# Self-Control and Commitment in Consumer Credit Markets*

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**Abstract**

This paper studies the role of commitment devices in mitigating self-control problems in consumer credit markets. Using a unique dataset from a large peer-to-peer lending platform, we examine a policy innovation that introduced a "direct-pay" disbursement option for debt refinancing loans. Under this option, loan proceeds are transferred directly to existing creditors, limiting borrowers' impulsive spending and thus serving as a commitment device. At the same time, borrowers can self-select between the direct-pay option and the regular "cash" option, which helps screen for more creditworthy individuals. Using a difference-in-differences design, we find that the introduction of the direct-pay option reduces default rates among eligible borrowers by 11%. Direct-pay adopters experience a 51% reduction in default relative to their counterfactual default risk absent the commitment device, indicating substantial behavioral improvement. Building on these empirical findings, we develop and estimate a dynamic structural model of borrowers' disbursement and repayment choices. Counterfactual simulations indicate that self-control problems account for approximately 39% of pre-policy defaults, and that the direct-pay policy reduces the aggregate default rate from 5.7% to 5.0%. Of the 3.2 percentage point gap in default rates between cash and direct-pay borrowers, 13% is attributed to selection and 87% to behavioral improvement. These results suggest that self-control is an important behavioral friction in consumer financial decisions and that commitment devices can help generate economically significant improvements in repayment outcomes.

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# 1 Introduction

Personal and household debt in the United States has surged to unprecedented levels, posing significant risks to financial stability. By mid-2024, total household debt reached a record $4.9 trillion (excluding housing debt), with credit card balances alone surpassing $1.1 trillion.[1] This has fueled a boom in the consumer finance market for debt refinancing, as households increasingly turn to personal loans to consolidate high-interest obligations. This segment has also experienced record growth, with unsecured personal loan balances reaching $245 billion by early 2024.[2] While often marketed as a tool for financial prudence, this borrow-to-repay behavior can create a "debt trap." Borrowers may consolidate their debts only to immediately accumulate new ones, often due to underlying issues with overspending.[3] This paper argues that the phenomenon arises not merely from financial literacy deficits but is reinforced by behavioral frictions, most notably self-control problems which create a persistent gap between a borrower's long-term financial intentions and their short-term spending impulses.

While traditional models of consumer credit focus on asymmetric information (e.g., Stiglitz and Weiss 1981), namely adverse selection and moral hazard, self-control problems represent a fundamentally different friction. Rather than arising from conflicts of interest between lenders and borrowers, self-control reflects an internal conflict within the borrower that turns out to align the incentives of the principal and the agent: both lenders, who seek to reduce default risk, and borrowers, who value financial stability, share an interest in mitigating it. This paper provides novel field evidence on this friction by studying a unique policy innovation from a large peer-to-peer (P2P) lending platform. To combat the misuse of funds, the platform introduced a "direct-pay" option for borrowers seeking to refinance existing debt at a discounted interest rate. This option transfers the loan proceeds directly to the borrower's existing creditors, such as commercial banks or credit card companies, bypassing the borrower's bank account, and thus functions as a commitment device to curb impulsive spending.[4]

[1] See the Quarterly Report on Household Debt and Credit by the Federal Reserve Bank of New York: https://www.newyorkfed.org/microeconomics/hhdc.

[2] See the Q1 2024 Quarterly Credit Industry Insights Report (CIIR) by TransUnion: https://www.transunion.com/blog/q1-2024-credit-industry-insights-report.

[3] For example, the approval of P2P lending has been shown to lead to more bankruptcy filings, suggesting that borrowers may overextend themselves financially and fall into "debt traps" (Wang and Overby 2022).

[4] Debt refinancing, where borrowers seek new loans to service existing debt, could be motivated by several considerations. First, a borrower might be temporarily liquidity-constrained and need to borrow to service an existing repayment obligation. Second, a borrower might want to consolidate multiple accounts into one for easier management. Third, if the platform offers a lower interest rate, a borrower could take advantage of the interest differential and save on interest repayment. Note that the direct-pay policy differs

We develop a theoretical framework to formalize this institutional setting, focusing on three core components: the self-control problem, the commitment device, and contract design under asymmetric information. We apply the classic quasi-hyperbolic discounting framework to a multi-period debt refinancing decision. This captures the central behavioral friction: a conflict between the borrower's ex-ante "planner" self at $t = 0$, who intends to use the loan responsibly, and the ex-post "doer" self at $t = 1$, who receives the cash and is tempted by immediate consumption. Our model formalizes this preference reversal, showing how the doer self can subvert the planner's optimal intention. The direct-pay option functions as a commitment device by allowing the planner self to preemptively restrict the future self's choice set. Crucially, we assume borrowers are sophisticated—aware of their own time-inconsistency. This sophistication creates an endogenous demand for commitment: the planner self, anticipating the doer's costly mistake, voluntarily chooses the direct-pay option at $t = 0$, thereby aligning the ex-post action with the ex-ante plan.

Beyond being a behavioral intervention, the direct-pay option also functions as an informational innovation in a market with asymmetric information. We model a borrower's unobserved "type" as their private cost of default. Borrowers with high default costs are more creditworthy and intend to repay, whereas those with low default costs are more prone to default. The direct-pay option functions as a screening device because the two types value it differently. High-types, who are both creditworthy and behaviorally sophisticated, gain significant utility from the commitment. Low-types, who have no intention to repay, gain nothing and prefer the liquidity of cash. By offering a menu of contracts, the platform induces a separating equilibrium: high-types self-select into the commitment, signaling their quality.

The theoretical framework yields clear, testable implications for borrower sorting and repayment outcomes, which we examine using a unique dataset of loans from the platform covering the period before (2017) and after (2018) the policy's introduction. We first use a difference-in-differences (DiD) design, exploiting the fact that the policy was available only for refinancing loans (treated) and not for general-purpose loans (control). In this design, eligibility for the direct-pay option is the treatment, regardless of whether a borrower actually adopts it, so the DiD coefficient captures an intent-to-treat (ITT) effect of making the commitment device available. We find that the introduction of the direct-pay option significantly reduced default rates for eligible borrowers by 11%. This policy

from a "balance transfer" in the context of credit card lending, which is typically adopted by commercial banks to attract customers from competitors. Personal loans for debt refinancing are primarily offered by digital lenders and fintech companies (such as LendingClub, SoFi, and Upstart).

effect is strongest among borrowers with lower FICO scores but higher incomes, consistent with the policy targeting those with the means to repay but lacking the discipline to do so, rather than those who are simply liquidity constrained.

In addition to estimating the policy's aggregate effect, we compare default rates between borrowers who adopt the direct-pay option and those who choose the cash option. The one-year default rate among direct-pay borrowers is 2.6%, substantially lower than that of cash borrowers at 6.2%. This difference reflects both the behavioral effect of the commitment device and the selection of more creditworthy borrowers into the direct-pay option. To disentangle these channels, we use the 2017 pre-policy cohort, when only the cash option was available, as a common benchmark. We find that 2018 cash borrowers perform significantly worse than the 2017 baseline pool, indicating that higher-quality borrowers sorted out of the cash pool and into the direct-pay option, consistent with adverse selection predicted by the model. We further show that the performance improvement among 2018 direct-pay adopters exceeds what selection alone can explain. The remaining improvement reflects the behavioral effect of the commitment device and can be interpreted as a treatment-on-the-treated effect. A back-of-the-envelope calculation, shown in Figure 2, indicates that direct-pay adopters reduce their default rates by approximately 2.7 percentage points, or about 51%, relative to their counterfactual default risk absent the commitment device.

Building on these empirical findings, we develop and estimate a dynamic structural model of borrowers' disbursement and repayment choices. In the model, borrowers have a private cost of default and choose between the cash option and the direct-pay option at loan origination. The key trade-off is that the cash option permits immediate discretionary spending but increases the debt burden in subsequent repayment periods. After loan origination, borrowers make monthly repayment decisions within a dynamic discrete choice framework. In estimation, we incorporate rich borrower and loan characteristics that affect both the distribution of borrower types and their propensity to consume.

We estimate the structural parameters by matching four key moments that capture the policy's impact: the 2017 pre-policy default rate as a baseline, the 2018 direct-pay take-up rate, which identifies selection, and the separate 2018 default rates for cash and direct-pay borrowers, which allow us to disentangle selection from behavioral effects. Based on our estimates, the default cost is $2.7 thousand for low-type borrowers and $4.5 thousand for high-type borrowers. As expected, borrowers with higher annual income, higher FICO scores, lower debt-to-income ratios, and longer credit histories are more likely to be creditworthy. We also find that, on average, borrowers allocate approximately 34.4% of cash loan proceeds to discretionary consumption, which amplifies future repayment burdens and contributes to default risk in the absence of commitment.

Using our structural estimates, we conduct a set of counterfactual experiments to (1) quantify the role of self-control problems, (2) evaluate the overall impact of the direct-pay option and decompose its selection and behavioral effects, and (3) assess alternative policy implementations. Counterfactual simulations indicate that self-control failures are an important driver of default, accounting for approximately 39% of all defaults in the pre-policy market. We also find that the direct-pay policy is effective, reducing the aggregate default rate from 5.7% to 5.0%. Moreover, the behavioral improvement induced by the commitment device, net of selection, is substantial. Of the 3.2 percentage point gap in default rates between cash and direct-pay borrowers, 13% is attributed to selection and 87% to behavioral improvement.

Finally, we compare the current policy with alternative implementations of the direct-pay option. We consider a "zero-discount" policy that introduces direct pay without an interest rate discount and find that it reduces the aggregate default rate to 5.4%, less than half the effect of the current policy. The smaller impact is primarily driven by lower take-up, highlighting the importance of the interest rate discount in encouraging adoption of the commitment device. Although the discount lowers interest rates, the resulting reduction in default risk may offset the loss in interest revenue, implying that lenders' expected returns could increase. We also evaluate a mandatory direct-pay policy and find that it could further reduce the default rate to 3.4%, representing a 1.6 percentage point improvement relative to the current policy.

Overall, our findings suggest that self-control problems are a quantitatively important friction in consumer financial decisions and that contract designs addressing this issue, such as limiting borrowers' ex post choices over the use of loan proceeds, can improve borrower outcomes while potentially increasing lender profitability.

**Related literature.** Our research is situated at the intersection of three distinct but related streams of literature: (1) the broad and growing field of behavioral household finance, which identifies cognitive biases as key drivers of financial outcomes; (2) the theoretical and empirical work on commitment devices as a solution to these biases; and (3) the classic literature on contract design and screening under asymmetric information.

This paper adds to the growing literature on behavioral household finance, which has moved beyond traditional life-cycle models to incorporate psychological frictions in explaining household financial decisions (Campbell 2006; Hirshleifer 2015; Zinman 2015). Seminal reviews by Beshears et al. 2018 and Gomes, Haliassos, and Ramadorai 2021 document a wide range of sub-optimal behaviors, including in household liability management, that are difficult to reconcile with the standard model. Our work focuses on the high-stakes consumer credit market, which has been reshaped by fintech platforms (Fuster et al. 2019; Buchak et al. 2018; Jagtiani, Lemieux, and Goldstein 2023). We posit that the "debt trap" phenomenon, where borrowers use refinancing loans for immediate consumption instead of debt repayment, is a direct and costly manifestation of these behavioral frictions.

The specific friction we analyze is the self-control problem, rooted in the "planner-doer" framework of time-inconsistent preferences (Thaler and Shefrin 1981; Laibson 1997; O'Donoghue and Rabin 1999). This conflict can lead to over-borrowing and default. Empirical work establishes that present-biased preferences correlate with credit card borrowing and debt accumulation (Meier and Sprenger 2010; Meier and Sprenger 2013; Allcott et al. 2022; Kuchler and Pagel 2021), and that self-control predicts financial behavior and well-being (Gathergood 2012; Strömbäck et al. 2017; DellaVigna 2009). The theoretical literature shows that firms design contracts to exploit these biases (DellaVigna and Malmendier 2004; Heidhues and Kőszegi 2010), while consumers may demand commitment devices to constrain future choices (Gul and Pesendorfer 2001; Galperti 2015; Toussaert 2018; Attanasio, Kovacs, and Moran 2020; Martinez, Meier, and Sprenger 2023). We contribute to this literature by studying self-control problems in personal loan and fintech lending and quantifying the impact of this friction using a structural model.

A second stream of literature examines commitment devices as a solution for sophisticated agents who are aware of their self-control problems (Bryan, Karlan, and Nelson 2010). This literature provides extensive field evidence showing that voluntary commitment mechanisms can improve outcomes in domains like workplace productivity (Kaur, Kremer, and Mullainathan 2015; Augenblick, Niederle, and Sprenger 2015), health (Giné, Karlan, and Zinman 2010; Schilbach 2019; Derksen et al. 2025; Avery, Giuntella, and Jiao 2025), and savings (Thaler and Benartzi 2004; Ashraf, Karlan, and Yin 2006; Beshears et al. 2020). This literature is thinner in the context of debt repayment. A closely related paper by Vihriälä 2023 finds that households voluntarily forgo payment flexibility to create self-imposed liquidity constraints. Our contribution is distinct: we study a setting where borrowers actively adopt an external device (the direct-pay option) to eliminate the flexibility of cash disbursement, providing direct field evidence of the demand for and efficacy of commitment in a high-risk credit market.

Finally, our work integrates this behavioral framework with the classic literature on asymmetric information and screening in credit markets. Beginning with Akerlof 1970, Rothschild and Stiglitz 1976, and Stiglitz and Weiss 1981, this literature demonstrates how lenders use contract terms to screen unobserved borrower "types" and mitigate adverse selection. This remains a central theme in modern consumer finance, where contract menus (e.g., loan maturity or pricing) are designed to induce separation (Einav, Jenkins, and Levin 2012; Galperti 2015; Kawai, Onishi, and Uetake 2022; Xin 2025; Yannelis and Zhang 2023; Agarwal et al. 2023; Polo, Taburet, and Vo 2025). The main innovation of our paper is the introduction of self-control problems, which generates shared interests between the principal and the agent. The direct-pay mechanism we analyze increases market efficiency by decreasing the probability of borrowers misusing funds for discretionary spending and promoting trust and cooperation between borrowers and lenders. We bridge these two frameworks by estimating a structural model that simultaneously features unobserved borrower heterogeneity and self-control problems, allowing us to separately quantify the selection and behavioral channels that drive the policy's effectiveness.

# 2 Institutional Background and Data

## 2.1 Personal Loans

We draw on data from a large US online financial services company (the "*platform*") that offers personal loans. The platform initially focused on lower-prime borrowers with limited access to brick-and-mortar bank credit, but in recent years has expanded to a broader customer base with stronger credit profiles. Borrowers can request unsecured loans of up to $40,000 with terms of either 3 or 5 years.[5] Loans feature fixed interest rates and equal monthly installments determined at origination. The platform charges an origination fee as a percentage of the loan amount, while interest income accrues to investors.[6]

To apply for a loan, a prospective borrower first specifies the desired amount and term, then provides additional information to the platform, including the stated purpose of the loan, home address, social security number, employment details, and income. Around 80% of borrowers on the platform seek loans to refinance existing debts, meaning they already hold credit card balances or personal loans and are borrowing to repay these obligations. This borrow-to-repay behavior can arise for several reasons, such as short-term

[5] A concern is that opportunistic borrowers might exploit P2P lending by borrowing with the deliberate intention of defaulting. To mitigate this risk, the platform requires borrowers to have at least three years of credit history and a minimum FICO score of 660 (often considered "fair" or "good" on the 300-850 scale). In the data, very few borrowers default in the first payment period, indicating that the borrower pool is reasonably creditworthy.

[6] This study focuses on the borrower side of the market, examining self-control problems and borrowers' commitment to responsible financial behavior. We abstract from the incentives and behavior of the platform and investors. Although the platform does not earn interest income directly, it remains strongly incentivized to screen for creditworthy borrowers to preserve its appeal to investors.

liquidity needs, more favorable terms offered by the platform, or a desire to consolidate multiple debts for easier management. The platform does not require borrowers to justify their specific motivation for debt refinancing.

The platform then retrieves the borrower's credit report from a consumer credit reporting agency to determine loan eligibility. If the borrower meets the underwriting criteria, the platform sets the interest rate using an internal algorithm based on the borrower's credit history and repayment capacity. Unlike some peer-to-peer lending models where borrowers and investors negotiate rates, loans on this platform are issued at interest rates unilaterally determined by the platform. After observing the quoted rate, the borrower decides whether to accept the terms. If the loan is accepted, the listing is posted on the platform's website, where individual (retail) investors can browse approved loans and invest based on the borrower's information. A key feature of this P2P market is that investors can purchase fractional shares of loans, and a loan is originated only once it is fully funded.

## 2.2 Direct-Pay Disbursement

If a borrower's loan application is approved, the loan amount is deposited into their bank account. Afterward, there is no effective mechanism for the platform or lenders to verify whether the funds are actually used for the stated purpose at application. Borrowers may genuinely intend to consolidate existing debts, but once they receive the cash, they can divert the money to other uses. This behavior can undermine their financial health and increase default risk for lenders.

To combat loan misuse and help borrowers follow through on their initial intentions, the platform introduced a new policy. Traditionally, loans were disbursed as cash deposits into the borrower's personal bank account. In 2018, the platform added an alternative disbursement method, the *direct-pay* option, which wires the loan proceeds directly to the borrower's other creditors, such as banks or credit card issuers. In practice, after submitting a loan request and the required information, borrowers are offered a choice between cash and direct-pay. The cash option works as before, while the direct-pay option requires borrowers to provide account details for their third-party creditors so that the platform can transfer funds on their behalf.

To encourage take-up of the direct-pay option, the platform offers an interest rate discount to borrowers who select it. The size of the discount is determined by an internal algorithm based on the borrower's credit history and repayment capacity. There are three main rationales for this discount. First, borrowers value the flexibility and liquidity of cash, which allows them to smooth consumption over time. Second, as with any new product, there is adoption friction: borrowers may hesitate to choose an unfamiliar option even when it is beneficial. Third, the discount serves as a screening device, because more creditworthy borrowers are generally more responsive to price incentives. We formalize this third channel in the structural model in Section 5.

### 2.3 Data

Our primary dataset consists of personal loans originated on the platform in the United States during 2017 and 2018, covering the period before and after the introduction of the direct-pay option.[7] We focus on debt-refinancing loans declared for "credit card repayment" or "debt consolidation", which represent approximately 80% of the platform's loans. The remaining loans are general-purpose consumption loans (e.g., weddings, holidays) that serve as the control group. The data include detailed loan terms and borrower characteristics, such as annual income, home ownership, debt-to-income ratio, credit score (FICO), delinquency record, and credit history length, that capture borrowers' repayment ability and creditworthiness. We track monthly repayment behavior through the beginning of 2020. For robustness checks, we also include loans from the 2014-2016 period.

Table 1 presents summary statistics for loans originated in 2018. Each loan is characterized by loan amount, term (3 or 5 years), disbursement option (cash or direct-pay), contractual interest rate, and any discount offered for the direct-pay option.[8] The sample shows an average loan amount of approximately $16,000, with 65% of loans having a 3-year term. About 20% of all loans (a quarter among those who are eligible) use the direct-pay disbursement method. Across all credit grades, the average interest rate is 13%, with direct-pay loans receiving an average discount of 3.5 percentage points.

For repayment outcomes, we observe partial repayment histories through early 2020.[9] The number of observed repayments varies depending on when the loan was issued dur-

[7] All loans are fully funded and observations are made at the loan level rather than at the individual borrower level. Coarse matching based on borrower characteristics (such as zip code, job title and length, and income) indicates that repeated borrowing is uncommon during the sample period.

[8] We do not directly observe the interest rate discount for choosing the direct-pay option. To address this issue, we use a random forest algorithm to estimate the relationship between the contractual interest rate, the disbursement option, and other key loan and borrower characteristics. We then predict the interest rate for the non-chosen disbursement method for each loan and use this to calculate the interest rate discount for the direct-pay option.

[9] Although the dataset includes information from early 2020, the onset of COVID-19 significantly disrupted household consumption and financial behavior. To avoid confounding effects, we choose not to conduct a more detailed analysis of this period.

Table 1: Summary Statistics

| Variable | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| *Loan characteristic* | | | | | |
| Loan amount (1,000s) | 339,662 | 15.64 | 9.88 | 1.00 | 40.00 |
| Term (1 = 3-year, 0 = 5-year) | 339,662 | 0.66 | 0.47 | 0.00 | 1.00 |
| Debt consolidation | 339,662 | 0.82 | 0.38 | 0.00 | 1.00 |
| Direct-pay | 339,662 | 0.19 | 0.40 | 0.00 | 1.00 |
| Contractual interest rate | 339,662 | 13.78 | 4.59 | 5.31 | 27.27 |
| Discount | 339,662 | 3.45 | 2.08 | 0.00 | 17.58 |
| *Repayment outcome* | | | | | |
| Default (in 1st year) | 339,662 | 0.057 | 0.23 | 0.00 | 1.00 |
| *Borrower characteristic* | | | | | |
| Annual income (1,000s) | 339,662 | 81.05 | 94.53 | 1.90 | 9930.48 |
| Home ownership (1 = yes) | 339,662 | 0.12 | 0.33 | 0.00 | 1.00 |
| Debt-to-income ratio (DTI) | 339,662 | 18.19 | 8.74 | 0.00 | 39.99 |
| Credit score (FICO) | 339,662 | 700.46 | 28.97 | 664.00 | 850.00 |
| Credit history length (years) | 339,662 | 15.72 | 7.71 | 3.17 | 69.00 |
| Credit inquiries (past 6 months) | 339,662 | 0.48 | 0.75 | 0.00 | 5.00 |
| Open credit accounts | 339,662 | 11.52 | 6.01 | 0.00 | 101.00 |
| Revolving credit utilization | 339,662 | 47.49 | 24.16 | 0.00 | 183.80 |

*Notes:* This table reports summary statistics for the main variables used in the analysis. The sample includes all approved loans originated in 2018. Variable definitions are as follows: Default equals one if the loan defaults within one year of origination; Direct-Pay equals one if the loan proceeds are disbursed directly to creditors; Loan Amount is measured in thousands of dollars; Interest Rate is expressed in percent; Annual Income is in thousands of dollars; Debt-to-Income (DTI) ratio, Credit Score (FICO), Credit History Length, Open Credit Accounts, and Revolving Utilization are as reported by the platform.

ing 2017-2018. To ensure comparability across all loans, we take a conservative approach and report loan status (either current, paid off, or defaulted) one year after origination. The first-year default rate in the sample is approximately 5%.[10]

Borrower characteristics reveal a mixed credit profile. The average debt-to-income ratio is 18.2%, indicating nontrivial debt burdens. Only 12% of borrowers are homeowners, and average annual income is approximately $81,000. The average FICO credit score is 700, placing borrowers in the “good” credit range. Borrowers have an average credit history length of 15.7 years and hold 11.5 open credit accounts on average. Revolving credit utilization averages 47.5%, suggesting borrowers are carrying substantial credit card debt,

[10]By the end of the sample period in early 2020, approximately 40% of the loans had concluded, either being paid off or defaulted. Among these, about a quarter were defaults.

which aligns with their stated purpose of debt refinancing.

# 3 Theoretical Framework

This section develops a multi-period model of debt refinancing behavior in the presence of self-control problems. The framework captures the tension between ex-ante financial discipline and ex-post temptation that arises when loan proceeds are disbursed as cash. The analysis builds on the classic model of present-biased preferences with quasi-hyperbolic discounting (Laibson 1997; O'Donoghue and Rabin 1999). In such settings, an agent's ex-post preferences can diverge from ex-ante intentions, leading to dynamically inconsistent choices.

## 3.1 Model Setup

At $t = 0$, the borrower faces an outstanding debt of size $s$. The borrower requests a refinancing loan of the same amount $s$, intended for debt restructuring.[11] No consumption occurs during this period.

At $t = 1$, the refinancing loan is disbursed with a term of $T$. Although the loan is intended for debt repayment, the disbursement is made in cash unless otherwise constrained. The borrower then faces the following choices: (1) *abstain*, applying the funds toward debt repayment as intended, or (2) *spend*, diverting a proportion $\alpha$ of the loan to discretionary consumption. If the borrower abstains, the new debt burden remains $s$. If the borrower spends, the debt burden increases to $(1 + \alpha)s$. We initially assume that the propensity to spend, $\alpha$, is exogenous.

For all subsequent periods $t \geq 2$, the borrower enters a dynamic repayment subgame, choosing monthly whether to make the installment payment or to default. Defaulting incurs a private cost $c > 0$, representing the economic and reputational consequences, such as future credit exclusion or collection penalties. This cost $c$ serves as our measure of a borrower's underlying creditworthiness. Importantly, this cost is unobservable to the lender and is thus the borrower's private information, or *type*, in the context of asymmetric information and adverse selection (Akerlof 1970; Rothschild and Stiglitz 1976).

The borrower's intertemporal utility at time $t$ is given by a quasi-hyperbolic discount-

[11] For simplicity, we assume the refinancing loan amount $s$ equals the outstanding debt. This assumption maps directly to our empirical implementation, where we observe borrowers requesting loans of size $s$ for debt refinancing but lack detailed information on their pre-existing debt obligations.

ing function:

$$U_t(x_t, x_{t+1}, \cdots, x_T) = u(x_t) + \beta \sum_{s=t+1}^{T} \delta^{s-t} u(x_s), \tag{1}$$

where $\delta$ is the standard exponential discount factor and $\beta \leq 1$ captures their *present bias*. When $\beta = 1$, preferences are *time-consistent*. Conversely, when $\beta < 1$, the agent exhibits a present bias, over-weighting immediate gratification relative to all future utilities.[12]

We analyze the borrower's decision from two distinct temporal perspectives: ex-ante (the "planner" self at $t = 0$) and ex-post (the "doer" self at $t = 1$). Let $V_1(s, r, c)$ denote the continuation value from the perspective of period $t = 1$ prior to the repayment subgame, given the principal $s$, interest rate $r$, and default cost $c$. This $V_1(\cdot)$ is the outcome of the dynamic repay-vs-default problem, which we leave unspecified for now and assume it to be well-behaved and differentiable. The borrower's choice between spending and abstaining leads to two possible continuation values

$$\begin{cases} V_1^{\text{spend}} = V_1((1+\alpha)s, r, c) & \text{if spend,} \\ V_1^{\text{abstain}} = V_1(s, r, c) & \text{if abstain.} \end{cases} \tag{2}$$

From the $t = 0$ ("planner" self) perspective, when he submits the loan request, all potential outcomes are in the future and are thus discounted. The utilities following either action are

$$\begin{cases} U_0^{\text{spend}} = \beta(\delta u(\alpha s) + \delta^2 V_1^{\text{spend}}) & \text{if spend,} \\ U_0^{\text{abstain}} = \beta \delta^2 V_1^{\text{abstain}} & \text{if abstain.} \end{cases} \tag{3}$$

From the $t = 1$ ("doer" self) perspective, after receiving the loan, the utility from consumption $u(\alpha s)$ is now immediate and is not discounted, while the future consequences

[12] The model assumes borrowers are fully *sophisticated*: aware of their time inconsistency and capable of anticipating future deviations from ex-ante plans (O'Donoghue and Rabin 2001). This assumption is most plausible for direct-pay adopters, whose choice reveals anticipation of self-control problems. For cash borrowers, non-adoption could reflect multiple factors: low default costs (our primary explanation), naivete about self-control problems, true time-consistency ($\beta \approx 1$), or liquidity preferences. Empirically, we cannot separately identify these channels. The fact that 2018 cash borrowers perform worse than the 2017 baseline suggests adverse selection (low-types) rather than naive high-types, supporting our focus on default cost as the primary sorting dimension. Our model abstracts from naivete to isolate the commitment mechanism. In the structural estimation, we allow the cash option to have a fixed utility component, which captures inertia, liquidity preferences, or naivete. We focus our analysis on sophisticated borrowers who demand commitment, recognizing that non-adoption may reflect factors beyond our model's scope. See John 2020 for evidence on how naivete can lead to commitment failure.

$V_1$ remain discounted by $\beta\delta$. The utilities following either action are

$$\begin{cases} U_1^{\text{spend}} = u(\alpha s) + \beta\delta V_1^{\text{spend}} & \text{if spend,} \\ U_1^{\text{abstain}} = \beta\delta V_1^{\text{abstain}} & \text{if abstain.} \end{cases} \tag{4}$$

## 3.2 Self-Control Problem

A self-control problem exists if the borrower's preference for spending reverses between $t = 0$ and $t = 1$. This conflict is analyzed by comparing the "planner" self at $t = 0$ with the "doer" self at $t = 1$. Let $\Delta V_1 = V_1^{\text{abstain}} - V_1^{\text{spend}}$ be the net continuation value lost from discretionary spending.

At $t = 0$, the "planner" intends to abstain if the discounted future cost of spending outweighs its utility. At $t = 1$, the "doer" is tempted by immediate gratification. This "doer" will choose to spend if the immediate utility outweighs the present-biased discounted future cost. This conflict, where the ex-ante plan to abstain is overturned by the ex-post action to spend, defines the self-control problem. It arises precisely when the utility of gratification falls between the planner's and the doer's thresholds, as formalized in the following proposition.

**Proposition 1** (Self-control problems)**.** *A sophisticated borrower exhibits a self-control problem, i.e., $U_0^{abstain} > U_0^{spend}$ but $U_1^{spend} > U_1^{abstain}$, if their present-bias parameter $\beta < 1$ is sufficiently low such that the immediate gratification $\alpha s$ falls within the following region:*

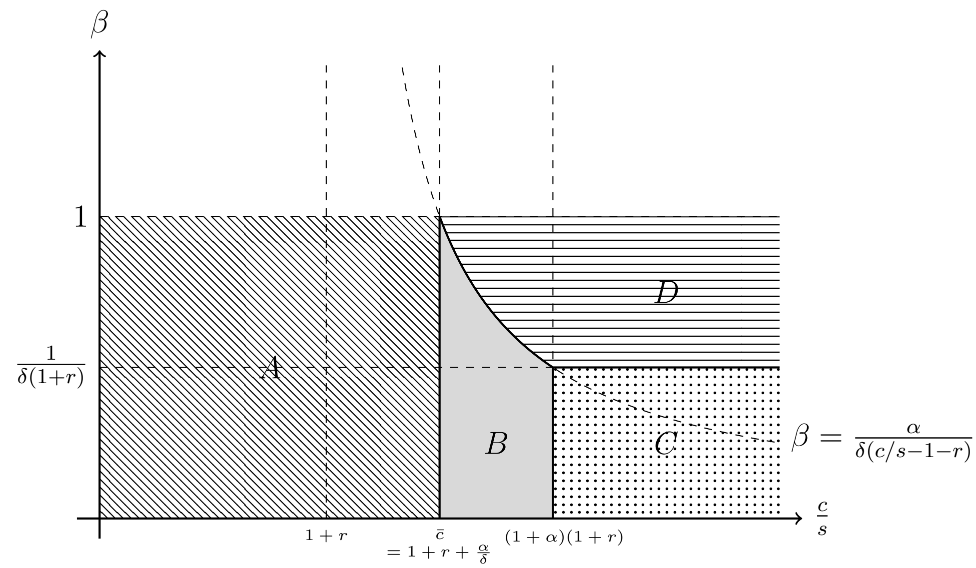
$$\beta\delta\Delta V_1 < u(\alpha s) < \delta\Delta V_1.$$

**Example.** We illustrate this tension in the following example. Consider a three-period model ($T = 2$) where the borrower has linear utility, $u(x) = x$. The repayment subgame at $t = 2$ consists of a single, binary choice: repay the loan (incurring the utility cost of the principal plus interest) or default (incurring the utility cost $-c$). The continuation values contingent on the spending decision are thus

$$\begin{cases} V_1^{\text{spend}} = \max\{-(1+\alpha)(1+r)s, -c\} & \text{if spend,} \\ V_1^{\text{abstain}} = \max\{-(1+r)s, -c\} & \text{if abstain.} \end{cases} \tag{5}$$

The borrower's optimal strategy depends on two key parameters: the present bias parameter $\beta$ and the default cost $c$ scaled by the loan size $s$. Figure 1 illustrates the parameter space based on these two dimensions. As detailed in the figure's notes, this space

Figure 1: Parameter Space of Default Cost ($c$) and Present Bias ($\beta$) in Example




*Notes:* This figure illustrates the borrower's optimal strategy in Example based on their present-bias parameter ($\beta$, y-axis) and their default cost scaled by the loan size ($c/s$, x-axis). Details of the derivation are given in Appendix A.1. The parameter space is divided into four regions:
Region A (Consistent defaulters): Borrowers with low default costs ($c/s$) who will default regardless of their spending decision. They plan to spend and default, and ex-post follow through.
Region D (Consistent repayers): Borrowers with high default costs ($c/s$) and high patience (high $\beta$). They plan to abstain from discretionary spending and repay, and ex-post follow through.
Regions B & C (Preference-reversing borrowers): Borrowers with moderate-to-high default costs but low patience (low $\beta$). Ex-ante (at $t = 0$), they prefer to abstain and repay. However, ex-post (at $t = 1$), their present bias causes them to reverse this preference and choose to spend. These are the borrowers who suffer from a self-control problem and thus have a demand for the direct-pay commitment device.

is divided into consistent (Regions A and D) and preference-reversing (Regions B and C) borrowers. Details of the parameter bounds are given in Appendix A.1.

Borrowers in Regions A and D exhibit consistent behavior: their ex-ante plans align with their ex-post choices. Borrowers in Region A (low cost) consistently plan to spend and default. Borrowers in Region D (high cost, high $\beta$) have no self-control problems and consistently plan to abstain and repay.

The key behavioral conflict, and the focus of our analysis, is captured by Regions B and C. These regions represent sophisticated borrowers who suffer from a self-control problem. Their behavior is driven by the interaction of two factors: (1) Moderate-to-high default cost ($c/s$) makes the future consequences of over-borrowing severe. From the ex-ante "planner" perspective at $t = 0$, the optimal plan is to abstain to avoid this high cost; (2) Low patience (low $\beta$) makes the immediate gratification of consumption highly salient. From the ex-post "doer" perspective at $t = 1$, this temptation outweighs the present-biased discounted future cost, causing the borrower to reverse their plan and spend. The regions differ in their repayment outcomes: Region C borrowers repay in period 2 despite spending, while Region B borrowers default in period 2.

The example highlights the central challenge in the refinancing market: while borrowers may ex-ante intend to use refinancing responsibly, the ex-post disbursement of cash exposes those with low patience to self-control failures. The model thus underscores the value of commitment mechanisms that can align these borrowers' ex-post actions with their ex-ante intentions.

## 3.3 Direct-Pay and Commitment Device

The direct-pay option functions as a commitment device to help borrowers preemptively restrict their future choices. At the time of loan origination ($t = 1$), borrowers are offered a binary choice between two disbursement methods: cash or direct-pay. Under the cash option, the borrower receives the funds directly, thereby retaining the opportunity to divert a portion ($\alpha > 0$) to immediate discretionary consumption in period $t = 1$. Under the direct-pay option, the lender bypasses the borrower and remits the funds directly to outstanding creditors. This action eliminates the possibility of discretionary spending altogether.[13]

The intervention is designed to target sophisticated borrowers in Regions B and C who exhibit preference reversal and correctly anticipate their ex-post deviation from their ex-ante plan. This anticipation creates an endogenous demand for commitment. For the sophisticated planner, the utility loss from their future self's mistake is a salient and predictable cost. The direct-pay option provides a mechanism to mitigate this cost. By voluntarily selecting the direct-pay contract at $t = 0$, the sophisticated borrower makes a rational, ex-ante decision to preemptively restrict their future self's choice set. This action aligns their ex-post behavior (forcing $\alpha = 0$) with their ex-ante intention, thereby maximizing the "planner" self's utility. [14]

This framework thus generates a sharp empirical test. In a world without self-control problems (i.e., $\beta = 1$), the direct-pay option would be behaviorally inert. Time-consistent borrowers either do not need commitment (Region D) or do not want it (Region A), so of-

[13]The commitment device we study eliminates the undesirable option entirely, rather than relying on incentives or penalties conditional on borrower actions. This approach contrasts with more traditional designs that depend on monitoring and enforcement; see Section 1 for a review of related work.

[14]A *naive* borrower, in contrast, would also be time-inconsistent but would *not* anticipate their $t = 1$ preference reversal. Believing they will "do the right thing," they would see no value in the direct-pay option and would not choose it, only to ex-post spend the funds. Our model's focus on sophistication provides a clear channel for voluntary take-up.

fering them this choice would have no aggregate impact on default rates. Therefore, any significant reduction in aggregate default rates following the policy's introduction is consistent with the mitigation of a pre-existing behavioral friction. The policy's effect, consequently, simultaneously provides field evidence for the existence of self-control problems and quantifies the welfare gains from their alleviation.

### 3.4 Contract Design and Borrowers' Self-Selection

Beyond its role as a commitment device, the direct-pay option also functions as a screening mechanism in the face of asymmetric information (Rothschild and Stiglitz 1976; Wilson 1977; Myerson 1981). From the lender's perspective, the borrower's default cost, $c$, is unobserved private information. This $c$ reflects the borrower's intrinsic creditworthiness, or "type." The introduction of contract choice alters this informational environment and allows the lender to address this information problem by inducing borrowers to self-select. The borrower's observable choice of disbursement method thus acts as a signal of their unobservable type.

This selection process can generate a separating equilibrium, analogous to classic models of contract design. To formalize the separation, consider the cutoff $\bar{c} = (1+r+\frac{\alpha}{\delta})s$ derived from the Example above. This threshold divides borrowers into two types based on their default costs. Low-cost borrowers ($c < \bar{c}$, e.g., Region A) are low-types who are prone to default. They have no incentive to restrict their future choices, are insensitive to the future debt burden, and place a high value on immediate liquidity; they will choose the cash option. High-cost borrowers ($c \geq \bar{c}$, e.g., Regions B and C) are high-types who intend to repay but are susceptible to self-control failures ($\beta < 1$). They face a strong incentive to opt into the direct-pay method, which provides commitment value to align their ex-post behavior with their ex-ante repayment intentions.

The example above illustrates the separation mechanism in a simplified setting; the result extends to the general model. Offering cash and direct-pay options generates a separating equilibrium at some threshold $\bar{c}$ dividing borrowers into low-cost types (cash) and high-cost types (direct-pay). For this separation to occur in the general case, the continuation value function $V_1(s,r,c)$ must satisfy the standard single-crossing condition in both $(s,c)$ and $(r,c)$. This condition holds naturally because high-cost borrowers are more responsive to changes in the total debt burden $s$ and interest rate $r$ precisely because they intend to repay.[15] The differential sensitivity enables separation: immediate consumption

[15]Formally, higher sensitivity means that the partial derivatives $\frac{\partial}{\partial s}V_1(s,r,c)$ and $\frac{\partial}{\partial r}V_1(s,r,c)$ (which are both negative) become more negative as $c$ increases, i.e., $\frac{\partial^2 V_1}{\partial s \partial c} < 0$ and $\frac{\partial^2 V_1}{\partial r \partial c} < 0$. This submodularity

utility $u(\alpha s)$ entices low-cost borrowers to choose cash, while high-cost borrowers prefer direct-pay for commitment value.

From a practical perspective, the lender can expand the set of borrowers choosing direct-pay by offering a lower interest rate for direct-pay borrowers, $r_d$, than that for cash borrowers, $r_c$. This discount serves two purposes. First, it ensures separation occurs: if rates are too high, the threshold $\bar{c}$ may exceed all borrowers' default costs, resulting in a corner solution where everyone chooses cash. Second, conditional on separation, the discount shifts the threshold downward, expanding the pool selecting direct-pay. Borrowers with moderate default costs who would have chosen cash at equal rates are now enticed by commitment value and lower repayment burden. We illustrate this effect in Figure A3 in Appendix A.1.

**Proposition 2** (Separating equilibrium by default cost)**.** *A contract menu consisting of cash disbursement at interest rate $r_c$ and direct-pay disbursement at interest rate $r_d$ induces a separating equilibrium at some cutoff $\bar{c}$ in which high-cost borrowers ($c \geq \bar{c}$) choose direct-pay and low-cost borrowers ($c < \bar{c}$) choose cash.*

This separation is not enforced externally but arises endogenously through the alignment of borrowers' private incentives and the constraints imposed by the policy. For lenders, observing which borrowers choose the commitment device provides a valuable informational cue, allowing them to infer the borrower's unobservable default risk. Thus, the direct-pay policy functions not only as a behavioral intervention but also as an informational innovation that enhances the efficiency of the credit market by reducing informational asymmetry. Empirically, however, this introduces complexity because a simple comparison of default rates between adopters and non-adopters is contaminated by selection bias. While this self-selection is a classic challenge for empirical identification, the mechanism itself provides a solution. By forcing an observable choice, the policy compels borrowers to reveal their private type not only to the lender but also to the econometrician.

# 4 Empirical Evidence

This section presents empirical evidence on how the introduction of the direct-pay disbursement option affects borrower behavior and loan performance. Guided by the theoretical framework, we test two key mechanisms through which the policy operates: (i) a selection channel, by which more creditworthy or self-aware borrowers self-select into

property satisfies single-crossing.

the commitment device, and (ii) a behavioral channel, through which the device directly mitigates self-control failures. We organize the analysis into four parts. We first examine the determinants of borrowers' choice of direct-pay, documenting who adopts the commitment device and why. We then exploit the staggered introduction of the policy across loan purposes to estimate its causal effect on default rates using a difference-in-differences design. Third, we analyze heterogeneity in treatment effects across borrower characteristics to identify segments most responsive to the policy. Finally, we conduct a decomposition analysis that separates the role of selection from behavioral improvement. Together, these results provide a comprehensive picture of how commitment devices shape credit outcomes in consumer loan markets.

## 4.1 Determinants of Direct-Pay Adoption

We begin by examining borrowers' take-up of the direct-pay disbursement option. Specifically, we estimate linear probability model (LPM) and logit specifications of the borrower's choice between the direct-pay and the cash disbursement methods:

$$Direct_i = \beta_1 Discount_i + X_i'\gamma + \mu_t + \epsilon_i, \tag{6}$$

where $i$ is the index for each loan, $Direct_i$ is an indicator of whether the borrower has chosen the direct-pay option, $Discount_i$ is the interest-rate reduction associated with the direct-pay option, $X_i$ includes borrower and loan characteristics, and $\mu_t$ denotes month-of-origination fixed effects. Table 2 reports eight specifications: Columns (1)–(4) present linear-probability estimates, and Columns (5)–(8) report the corresponding logit estimates. Each successive specification adds richer controls; Columns (4) and (8) include full borrower covariates and month fixed effects.

The estimates show a strong positive association between the offered discount and the likelihood of choosing direct-pay. A one-percentage-point larger discount raises the probability of adoption by about 5 percentage points after controlling for borrower characteristics and month effects. This elasticity confirms that borrowers respond predictably to the financial incentive embedded in the pricing menu. The negative coefficient on the undiscounted interest rate further suggests that, holding the discount constant, higher underlying rates discourage adoption.

Beyond the price incentive, adoption is systematically related to borrower balance-sheet characteristics. Borrowers with larger loan amounts and higher debt-to-income (DTI) ratios are significantly more likely to select direct-pay, consistent with the notion that borrowers facing heavier debt burdens have stronger motives to pre-commit to debt

Table 2: Determinants of Direct-Pay Adoption

| | Direct | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Discount | 0.015*** | 0.054*** | 0.056*** | 0.050*** | 0.093*** | 0.427*** | 0.444*** | 0.398*** |
| | (0.000) | (0.000) | (0.000) | (0.003) | (0.002) | (0.003) | (0.003) | (0.015) |
| Undiscounted interest rate | | −0.035*** | −0.044*** | −0.044*** | | −0.279*** | −0.362*** | −0.374*** |
| | | (0.000) | (0.000) | (0.004) | | (0.002) | (0.002) | (0.008) |
| Loan amount | | | 0.004*** | 0.004*** | | | 0.022*** | 0.023*** |
| | | | (0.000) | (0.000) | | | (0.001) | (0.001) |
| Term 3-year | | | −0.064*** | −0.066*** | | | −0.516*** | −0.544*** |
| | | | (0.002) | (0.010) | | | (0.013) | (0.054) |
| log(Annual income) | | | −0.059*** | −0.065*** | | | −0.476*** | −0.536*** |
| | | | (0.001) | (0.005) | | | (0.011) | (0.022) |
| Debt-to-income | | | 0.000** | 0.000 | | | 0.003*** | 0.002* |
| | | | (0.000) | (0.000) | | | (0.001) | (0.001) |
| Credit score (FICO) | | | −0.000*** | −0.001*** | | | −0.004*** | −0.005*** |
| | | | (0.000) | (0.000) | | | (0.000) | (0.001) |
| Home ownership | | | −0.006** | −0.002 | | | −0.036* | −0.005 |
| | | | (0.002) | (0.006) | | | (0.014) | (0.045) |
| Credit history length (years) | | | −0.002*** | −0.002*** | | | −0.016*** | −0.017*** |
| | | | (0.000) | (0.000) | | | (0.001) | (0.001) |
| Credit inquiries (past 6 months) | | | −0.006*** | −0.002* | | | −0.037*** | −0.011 |
| | | | (0.001) | (0.001) | | | (0.007) | (0.008) |
| Open credit accounts | | | 0.005*** | 0.005*** | | | 0.038*** | 0.041*** |
| | | | (0.000) | (0.000) | | | (0.001) | (0.001) |
| Revolving credit utilization | | | 0.002*** | 0.002*** | | | 0.018*** | 0.019*** |
| | | | (0.000) | (0.000) | | | (0.000) | (0.000) |
| Constant | 0.142*** | 0.510*** | 1.075*** | 1.073*** | −1.758*** | 0.920*** | 5.907*** | 5.785*** |
| | (0.001) | (0.003) | (0.023) | (0.144) | (0.009) | (0.019) | (0.175) | (0.743) |
| Month fixed effects | No | No | No | Yes | No | No | No | Yes |
| R2 | 0.006 | 0.073 | 0.104 | 0.131 | | | | |
| Observations | 339662 | 339662 | 339662 | 339662 | 339662 | 339662 | 339662 | 339662 |
| Log-likelihood | | | | | −166062.343 | −152923.651 | −147045.273 | −141752.550 |

*Notes:* This table reports estimates of borrowers' choices between the direct-pay and cash disbursement options. The dependent variable equals one if the borrower selects the direct-pay option and zero otherwise. Columns (1)–(4) present linear-probability models (LPM) and Columns (5)–(8) report logit specifications. Columns (4) and (8) include month-of-origination fixed effects. Robust standard errors clustered by origination month are reported in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

repayment and to avoid the temptation to spend newly borrowed funds. Conversely, higher-income borrowers are less likely to adopt, indicating that they value liquidity and flexibility more than the commitment benefit of direct-pay. The negative coefficients on FICO score, credit-history length, and homeownership imply that financially more established borrowers are less inclined to restrict their discretion, again consistent with smaller perceived self-control frictions in this group. Finally, borrowers with more open accounts or higher revolving utilization are more likely to choose direct-pay, reinforcing the interpretation that the option appeals to borrowers managing complex debt portfolios.

Taken together, these results show that both price incentives and behavioral motives drive adoption of the commitment device. The platform's design effectively screens borrowers along dimensions of indebtedness and liquidity preference: those with greater outstanding debt or potential self-control concerns self-select into the direct-pay option, whereas borrowers with stronger balance sheets or greater demand for flexibility favor cash disbursement. This heterogeneity in take-up lays the foundation for the analysis that follows, which examines how the introduction of the direct-pay feature affects default outcomes and whether its benefits arise from selection or from genuine behavioral improvement.

## 4.2 Effect of Policy Availability

We next assess the causal effect of the platform's introduction of the direct-pay option on borrower default. The policy became available in 2018 for refinancing loans, i.e., those used to consolidate or repay existing debts, but not for general-purpose loans such as home improvement or major purchases. This institutional feature allows us to implement a difference-in-differences (DiD) design that compares the change in default rates for eligible loans (refinancing) to that for ineligible loans (general-purpose consumption) before and after the policy introduction.

The difference-in-differences (DiD) design relies on the key assumption that eligible (treated) and ineligible (control) borrowers are comparable groups that would have followed parallel trends absent the policy. We first conduct a covariate balance test, reported in Table A9 in Appendix A.2. The treated and control groups are broadly similar across key observable dimensions, including income, FICO score, and credit history. Although eligible borrowers understandably have slightly higher debt burdens (DTI and revolving utilization), the overall comparability supports the validity of the DiD design. We now proceed with the DiD analysis.

Table 3: Effect of Direct-Pay Policy Introduction on Loan Default: Difference-in-Differences Estimates

| | One-year default | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post | 0.008*** | 0.008*** | 0.008*** | 0.138*** | 0.120*** | 0.120*** |
| | (0.001) | (0.001) | (0.002) | (0.022) | (0.023) | (0.035) |
| Treated | −0.009*** | −0.014*** | −0.014*** | −0.165*** | −0.256*** | −0.255*** |
| | (0.001) | (0.001) | (0.001) | (0.018) | (0.018) | (0.015) |
| Post × Treated | −0.007*** | −0.006*** | −0.006** | −0.114*** | −0.096*** | −0.098** |
| | (0.001) | (0.001) | (0.002) | (0.025) | (0.026) | (0.031) |
| Loan amount | | 0.001*** | 0.001*** | | 0.028*** | 0.028*** |
| | | (0.000) | (0.000) | | (0.001) | (0.001) |
| Term 3-year | | −0.005*** | −0.004*** | | −0.087*** | −0.086*** |
| | | (0.001) | (0.001) | | (0.013) | (0.015) |
| log(Annual income) | | −0.015*** | −0.015*** | | −0.307*** | −0.308*** |
| | | (0.001) | (0.001) | | (0.013) | (0.026) |
| Debt-to-income | | 0.001*** | 0.001*** | | 0.013*** | 0.013*** |
| | | (0.000) | (0.000) | | (0.001) | (0.001) |
| Credit score (FICO) | | −0.000*** | −0.000*** | | −0.007*** | −0.007*** |
| | | (0.000) | (0.000) | | (0.000) | (0.000) |
| Home ownership | | 0.003** | 0.003*** | | 0.049** | 0.049*** |
| | | (0.001) | (0.001) | | (0.016) | (0.009) |
| Credit history length (years) | | −0.001*** | −0.001*** | | −0.011*** | −0.010*** |
| | | (0.000) | (0.000) | | (0.001) | (0.001) |
| Credit inquiries (past 6 months) | | 0.018*** | 0.018*** | | 0.291*** | 0.290*** |
| | | (0.000) | (0.001) | | (0.006) | (0.009) |
| Open credit accounts | | −0.001*** | −0.001*** | | −0.016*** | −0.016*** |
| | | (0.000) | (0.000) | | (0.001) | (0.001) |
| Revolving credit utilization | | −0.000*** | −0.000*** | | −0.004*** | −0.004*** |
| | | (0.000) | (0.000) | | (0.000) | (0.000) |
| Constant | 0.061*** | 0.359*** | 0.357*** | −2.727*** | 3.134*** | 3.105*** |
| | (0.001) | (0.008) | (0.009) | (0.016) | (0.167) | (0.210) |
| Month fixed effects | No | No | Yes | No | No | Yes |
| R2 | 0.001 | 0.009 | 0.009 | | | |
| Observations | 660969 | 660969 | 660969 | 660969 | 660969 | 660969 |
| Log-likelihood | | | | −141719.546 | −139098.260 | −139082.471 |

*Notes:* This table reports difference-in-differences estimates of the effect of the direct-pay policy on borrowers' one-year default probability. The dependent variable equals one if the loan defaults within one year of origination. Post is an indicator for loans originated after the policy introduction in 2018. Treated equals one for loans whose stated purpose qualifies for the direct-pay option (debt-refinancing or credit-card-repayment loans) and zero for ineligible, general-purpose loans. The interaction term Post × Treated measures the policy's impact on default rates among eligible borrowers relative to ineligible ones. Columns (1)–(3) present linear-probability models, and Columns (4)–(6) report logit specifications; later columns add borrower covariates and month-of-origination fixed effects. Robust standard errors are clustered by origination month. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Formally, we estimate the following model:

$$Default_{it} = \alpha + \beta_1 Post_t + \beta_2 Treated_i + \beta_3(Post_t \times Treated_i) + X_{it}'\gamma + \epsilon_{it}, \qquad (7)$$

where $Default_{it}$ is an indicator equal to one if loan defaults within one year of origination, $Post_t$ equals one for loans originated after the policy (2018) and zero before the policy (2017), and $Treated_i$ equals one for loans whose stated purpose qualifies for the direct-pay option (e.g., refinancing) and zero otherwise (e.g., consumption loans). Note that being eligible does not mean that the borrower must use the direct-pay option. The coefficient of interest, $\beta_3$, measures the differential change in default rates for eligible versus ineligible loans following the policy introduction. In this specification, eligibility for the direct-pay option is the treatment, regardless of whether a borrower subsequently adopts it. We therefore interpret $\beta_3$ as an intent-to-treat (ITT) effect of making the commitment device available to eligible borrowers on their one-year default probability. We include borrower- and loan-level controls $X_{it}$ (loan amount, term, log income, debt-to-income ratio, and FICO score) and, in the preferred specification, month fixed effects $\mu_t$. Standard errors are clustered by month of origination to allow for arbitrary correlation in residuals across loans originated in the same month, capturing common shocks in underwriting standards, macro conditions, and other month-specific factors.

Table 3 reports the results. Across all specifications, the coefficient on the interaction term $Post \times Treated$ is negative and statistically significant, indicating that default rates declined for borrowers eligible for the direct-pay option relative to those who were not. In the preferred logit specification with full controls and month fixed effects (Column 6), the estimated coefficient of -0.098 corresponds to roughly a 0.6 percentage-point reduction in one-year default probability, relative to a pre-policy mean of about 5%. Economically, this represents an 11% decline in default risk attributable to the availability of the policy.

The main effects are also informative. The positive and significant coefficient on $Post$ shows that default rates increased slightly for ineligible loans after 2018, which is consistent with a modest deterioration in overall credit quality or macro conditions. The negative coefficient on $Treated$ indicates that refinancing loans, typically used to repay existing debts, exhibited a lower baseline default risk even before the policy. The incremental decline captured by $\beta_3$ thus reflects a true policy effect rather than compositional differences. The estimates are robust to including borrower covariates and month effects, confirming that the results are not driven by changes in borrower composition or time-specific shocks.

Together, these findings indicate that making the direct-pay option available improved repayment outcomes among eligible borrowers, which is consistent with the behavioral-commitment channel. The results are robust to alternative specifications and identification windows. In Table A11 in Appendix A.3, we extend the analysis by enlarging the pre-policy period to include loans originated between 2014 and 2017, re-estimating both the baseline difference-in-differences model and a time-varying treatment effect specification that traces dynamic responses to the policy introduction. The estimated effects remain negative and statistically significant across all specifications. Moreover, the event-study coefficients exhibit little pre-trend differences between treated and untreated groups, confirming that the parallel-trends assumption underlying the DiD design is satisfied. (See Figure A4 in Appendix A.3.) Consistent with these reduced-form default regressions, the survival analysis in Table A12 in Appendix A.3 shows that the direct-pay policy significantly lowers the hazard of default.

## 4.3 Heterogeneity

We next examine whether the effect of the direct-pay policy differs across borrower risk and liquidity profiles. Theory suggests that borrowers with greater self-control problems, but not necessarily tighter liquidity constraints, should benefit most from the commitment device. To test this prediction, we re-estimate the difference-in-differences specification separately by (i) credit quality, (ii) indebtedness, (iii) income, and (iv) revolving credit utilization. Specifically, we split the sample into three tiers of FICO score, two groups of debt-to-income (DTI) ratio (below- and above-median), three income tiers (bottom, middle, and top terciles), and three revolving utilization groups (low, medium, and high). Table 4 reports the results. All regressions include the same borrower- and loan-level controls as before and month-of-origination fixed effects.

Across subsamples, the estimated interaction coefficient Post × Treated remains negative for most groups, but its magnitude and significance vary systematically with borrower characteristics. The policy effect is strongest among low-FICO borrowers, where the coefficient of -0.010 (Column 1) implies roughly a one-percentage-point decline in one-year default probability relative to the pre-policy mean of about 10%. The effect diminishes with credit quality and becomes statistically insignificant in the higher-FICO terciles, consistent with the notion that high-score borrowers already exhibit greater financial discipline and hence have less scope for behavioral improvement. When splitting by debt-to-income ratio, the coefficient is negative and significant only for low-DTI borrowers (Column 4), suggesting that the policy is most effective for borrowers who are relatively liquid but prone to self-control failures rather than those already financially

Table 4: Heterogeneity in the Effect of the Direct-Pay Policy on Default

| | One-year default | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | FICO | | | DTI | | Income | | | Revolving utilization | | |
| | low (1) | medium (2) | high (3) | low (4) | high (5) | low (6) | medium (7) | high (8) | low (9) | medium (10) | high (11) |
| Post | 0.008* | 0.005 | 0.009** | 0.008*** | 0.002 | 0.006* | 0.004 | 0.011*** | 0.009** | 0.007*** | 0.003 |
| | (0.004) | (0.004) | (0.003) | (0.002) | (0.005) | (0.003) | (0.004) | (0.003) | (0.003) | (0.002) | (0.002) |
| Treated | −0.010*** | −0.016*** | −0.017*** | −0.014*** | −0.009* | −0.014*** | −0.016*** | −0.013*** | −0.011*** | −0.014*** | −0.011*** |
| | (0.001) | (0.002) | (0.002) | (0.001) | (0.004) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Post × Treated | −0.010** | −0.001 | −0.005 | −0.007** | −0.004 | −0.004 | −0.002 | −0.011*** | −0.002 | −0.007** | −0.005** |
| | (0.004) | (0.003) | (0.003) | (0.002) | (0.006) | (0.003) | (0.004) | (0.002) | (0.003) | (0.002) | (0.002) |
| Loan amount | 0.002*** | 0.001*** | 0.001*** | 0.002*** | 0.001*** | 0.002*** | 0.002*** | 0.001*** | 0.003*** | 0.001*** | 0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Term 3-year | −0.008*** | −0.004** | −0.001 | −0.004*** | −0.008*** | −0.004* | −0.004** | −0.002 | −0.001 | −0.007*** | −0.001* |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| log(Annual income) | −0.016*** | −0.014*** | −0.014*** | −0.016*** | −0.008* | −0.024*** | −0.014*** | −0.011*** | −0.023*** | −0.012*** | −0.012*** |
| | (0.002) | (0.002) | (0.001) | (0.001) | (0.003) | (0.002) | (0.004) | (0.001) | (0.002) | (0.001) | (0.001) |
| Debt-to-income | 0.001*** | 0.001*** | 0.000*** | 0.000*** | 0.001* | 0.001*** | 0.001*** | 0.001*** | 0.000** | 0.001*** | 0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Credit score (FICO) | −0.001*** | −0.000*** | −0.000*** | −0.000*** | −0.001*** | −0.000*** | −0.000*** | −0.000*** | −0.000*** | −0.001*** | −0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Home ownership | 0.001 | 0.003 | 0.005*** | 0.003*** | −0.001 | −0.002*** | 0.000 | 0.010*** | 0.002 | 0.002* | 0.004* |
| | (0.001) | (0.002) | (0.001) | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) |
| Credit history length (years) | −0.001*** | −0.000*** | −0.000*** | −0.001*** | −0.000 | −0.000 | −0.001*** | −0.001*** | −0.001*** | −0.000*** | −0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Credit inquiries (past 6 months) | 0.017*** | 0.017*** | 0.019*** | 0.018*** | 0.016*** | 0.019*** | 0.018*** | 0.016*** | 0.017*** | 0.016*** | 0.021*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Open credit accounts | −0.001*** | −0.001*** | −0.001*** | −0.001*** | −0.001*** | −0.001*** | −0.001*** | −0.001*** | −0.001*** | −0.001*** | −0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Revolving credit utilization | −0.000*** | −0.000*** | −0.000*** | −0.000*** | −0.000** | −0.000*** | −0.000*** | −0.000*** | −0.001*** | −0.000*** | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Constant | 0.474*** | 0.367*** | 0.262*** | 0.347*** | 0.475*** | 0.372*** | 0.378*** | 0.331*** | 0.344*** | 0.451*** | 0.411*** |
| | (0.039) | (0.052) | (0.010) | (0.009) | (0.028) | (0.017) | (0.022) | (0.015) | (0.018) | (0.013) | (0.017) |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| R2 | 0.008 | 0.008 | 0.012 | 0.009 | 0.007 | 0.009 | 0.010 | 0.010 | 0.015 | 0.008 | 0.008 |
| Observations | 276290 | 169450 | 215229 | 596244 | 64725 | 241624 | 186718 | 232627 | 185100 | 302233 | 173636 |

*Notes:* This table reports difference-in-differences estimates of the policy effect across borrower risk and liquidity groups. The dependent variable equals one if the loan defaults within one year of origination. Post is an indicator for loans originated after the 2018 introduction of the direct-pay policy. Treated equals one for loans whose stated purpose qualifies for the direct-pay option (debt-refinancing or credit-card-repayment loans). The coefficient on Post × Treated measures the change in default probability for treated (eligible) loans relative to untreated loans following the policy introduction. Columns (1)–(3) split the sample by FICO-score terciles (low, medium, high), Columns (4)–(5) by debt-to-income (DTI) ratio (below- and above-median), Columns (6)–(8) by income terciles (low, medium, high), Columns (9)–(11) by revolving utilization terciles (low, medium, high). All specifications include the full set of borrower- and loan-level controls, loan amount, term, log annual income, DTI, FICO, home ownership, credit-history length, credit inquiries in the past six months, number of open accounts, and revolving credit utilization, as well as month-of-origination fixed effects. Robust standard errors are clustered by origination month. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

constrained. Similarly, by income group, the policy has the largest and most significant impact among high-income borrowers (Column 8), while the effect is weaker and statistically indistinguishable from zero for the lower-income groups.

The revolving credit utilization results in Table 4 provide additional insight into which borrowers benefit most from the commitment device. The policy effect is strongest for borrowers with medium revolving utilization (Column 10), where the $Post \times Treated$ coefficient of about -0.007 is negative and statistically significant. In contrast, the effect is smaller and statistically insignificant for low-utilization borrowers (Column 9) and somewhat weaker, though still negative and significant, for high-utilization borrowers (Column 11). This pattern suggests that borrowers with moderate to high credit card debt are the primary beneficiaries of the commitment mechanism. These borrowers have the capacity to further increase their debt burden through discretionary spending, making them most vulnerable to self-control failures and thus most likely to benefit from the direct-pay option. High-utilization borrowers, who are already heavily indebted, may face binding liquidity constraints that limit their ability to spend further, tempering (but not eliminating) the gains from commitment.

The heterogeneity results indicate that the direct-pay option is most effective for borrowers who are liquid but risky: those with higher incomes, lower DTI ratios, weaker credit histories, and moderate revolving credit utilization. This pattern reinforces our interpretation that the policy mitigates self-control-driven defaults rather than easing binding credit constraints. The commitment device is most valuable for borrowers who have the financial means to repay but lack the discipline to resist further spending, particularly those with moderate existing credit card debt who are at risk of accumulating more.

## 4.4 Effect of Direct-Pay Adoption: Selection vs. Behavioral Channels

Having established that the policy's availability improved market-wide outcomes, we now examine the effect on those who adopted the direct-pay option among borrowers eligible for the policy. We begin with the cross-section of 2018 loans and estimate

$$Default_i = \beta Direct_i + X_i\gamma + \mu_t + \epsilon_i, \tag{8}$$

where $Direct_i$ is an indicator for the disbursement method, $X_i$ is a vector of borrower and loan controls, and $\mu_t$ denotes month-of-origination fixed effects.

Table Table 5a reports the estimates. The coefficient on Direct-Pay is -0.88, implying that, conditional on observables, choosing direct-pay reduces the odds of default by roughly 17 percent relative to cash disbursement. In levels, the one-year default rate

Table 5: Decomposition of Selection and Behavioral Effects

(a) Within-2018 Comparison of Direct-Pay and Cash Borrowers

| | One-year default | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Direct-pay | −0.035*** | −0.031*** | −0.032*** | −0.880*** | −0.795*** | −0.816*** |
| | (0.001) | (0.001) | (0.001) | (0.026) | (0.026) | (0.030) |
| Loan amount | | 0.001*** | 0.001*** | | 0.025*** | 0.025*** |
| | | (0.000) | (0.000) | | (0.001) | (0.001) |
| Term 3-year | | −0.006*** | −0.006*** | | −0.118*** | −0.113*** |
| | | (0.001) | (0.001) | | (0.019) | (0.016) |
| log(Annual income) | | −0.013*** | −0.014*** | | −0.277*** | −0.282*** |
| | | (0.001) | (0.001) | | (0.020) | (0.028) |
| Debt-to-income | | 0.000*** | 0.000*** | | 0.010*** | 0.010*** |
| | | (0.000) | (0.000) | | (0.001) | (0.001) |
| Credit score (FICO) | | −0.000*** | −0.000*** | | −0.008*** | −0.008*** |
| | | (0.000) | (0.000) | | (0.000) | (0.000) |
| Home ownership | | 0.001 | 0.001 | | 0.016 | 0.017 |
| | | (0.001) | (0.001) | | (0.026) | (0.024) |
| Credit history length (years) | | −0.001*** | −0.001*** | | −0.011*** | −0.011*** |
| | | (0.000) | (0.000) | | (0.001) | (0.001) |
| Credit inquiries (past 6 months) | | 0.017*** | 0.017*** | | 0.284*** | 0.284*** |
| | | (0.001) | (0.001) | | (0.010) | (0.016) |
| Open credit accounts | | −0.001*** | −0.001*** | | −0.017*** | −0.017*** |
| | | (0.000) | (0.000) | | (0.002) | (0.002) |
| Revolving credit utilization | | −0.000*** | −0.000*** | | −0.006*** | −0.005*** |
| | | (0.000) | (0.000) | | (0.000) | (0.000) |
| Constant | 0.062*** | 0.376*** | 0.369*** | −2.715*** | 3.598*** | 3.467*** |
| | (0.000) | (0.013) | (0.010) | (0.009) | (0.261) | (0.236) |
| Month fixed effects | No | No | No | No | Yes | Yes |
| R2 | 0.004 | 0.012 | 0.012 | | | |
| Log-likelihood | 278331 | 278331 | 278331 | 278331 | 278331 | 278331 |
| Observations | | | | −57570.105 | −56567.484 | −56535.076 |

among direct-pay borrowers averages 2.6 percent, compared with 6.2 percent for cash borrowers. This raw difference reflects both the selection of safer borrowers into direct-pay and the behavioral impact of pre-commitment.

This raw difference, however, presents a classic identification challenge. It is impossible to know from this comparison alone how much of the improvement is due to a behavioral effect (the commitment device making borrowers less risky) versus a selection effect (less risky borrowers choosing the device). To separate these two channels, we use the 2017 pre-policy cohort of debt-refinancing loans (i.e., those who would have been eligible to use the direct-pay option in 2018) as a baseline. Because we can observe the behavior of these baseline cash borrowers, we can characterize the mixture of underlying borrower types and their average default behavior before the option to self-select into direct-pay existed. The 2018 policy then splits this mixture into two observed sub-pools (cash and direct-pay), and comparing their default outcomes, both within 2018 and relative to the 2017 benchmark, provides the raw ingredients for decomposing selection and

Table 5: Decomposition of Selection and Behavioral Effects (cont.)

(b) Comparison with 2017 Baseline: Separating Selection and Commitment Effects

| | One-year default | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post cash | 0.010*** | 0.009*** | 0.009*** | 0.177*** | 0.169*** | 0.168*** |
| | (0.001) | (0.001) | (0.001) | (0.013) | (0.013) | (0.021) |
| Post direct-pay | −0.026*** | −0.022*** | −0.023*** | −0.703*** | −0.630*** | −0.644*** |
| | (0.001) | (0.001) | (0.001) | (0.026) | (0.026) | (0.027) |
| Loan amount | | 0.001*** | 0.001*** | | 0.025*** | 0.025*** |
| | | (0.000) | (0.000) | | (0.001) | (0.001) |
| Term 3-year | | −0.005*** | −0.005*** | | −0.103*** | −0.099*** |
| | | (0.001) | (0.001) | | (0.014) | (0.016) |
| log(Annual income) | | −0.013*** | −0.014*** | | −0.286*** | −0.288*** |
| | | (0.001) | (0.001) | | (0.015) | (0.026) |
| Debt-to-income | | 0.001*** | 0.001*** | | 0.015*** | 0.015*** |
| | | (0.000) | (0.000) | | (0.001) | (0.001) |
| Credit score (FICO) | | −0.000*** | −0.000*** | | −0.008*** | −0.008*** |
| | | (0.000) | (0.000) | | (0.000) | (0.000) |
| Home ownership | | 0.002 | 0.002* | | 0.032 | 0.031* |
| | | (0.001) | (0.001) | | (0.019) | (0.013) |
| Credit history length (years) | | −0.000*** | −0.000*** | | −0.010*** | −0.010*** |
| | | (0.000) | (0.000) | | (0.001) | (0.001) |
| Credit inquiries (past 6 months) | | 0.017*** | 0.017*** | | 0.285*** | 0.284*** |
| | | (0.000) | (0.001) | | (0.007) | (0.008) |
| Open credit accounts | | −0.001*** | −0.001*** | | −0.016*** | −0.016*** |
| | | (0.000) | (0.000) | | (0.001) | (0.002) |
| Revolving credit utilization | | −0.000*** | −0.000*** | | −0.004*** | −0.004*** |
| | | (0.000) | (0.000) | | (0.000) | (0.000) |
| Constant | 0.053*** | 0.372*** | 0.369*** | −2.892*** | 3.786*** | 3.732*** |
| | (0.000) | (0.009) | (0.007) | (0.009) | (0.198) | (0.181) |
| Month fixed effects | No | No | No | No | Yes | Yes |
| R2 | 0.002 | 0.010 | 0.010 | | | |
| Log-likelihood | 529346 | 529346 | 529346 | 529346 | 529346 | 529346 |
| Observations | | | | −109254.205 | −107333.666 | −107305.733 |

*Notes:* This table decomposes the decline in default associated with the direct-pay policy into selection and behavioral components. Table 5a estimates Equation (8) using 2018 loans only; the dependent variable equals one if the loan defaults within one year of origination. Direct-Pay equals one for loans disbursed directly to creditors and zero for cash disbursement. Table 5b estimates Equation (9) on pooled 2017–2018 data, with 2017 cash borrowers as the omitted group. Post Cash and Post Direct are indicators for 2018 cash and 2018 direct-pay loans, respectively. All regressions control for loan amount, term (3-year indicator), log annual income, debt-to-income ratio, FICO score, homeownership, credit-history length, credit inquiries in the past six months, number of open credit accounts, and revolving-credit utilization, and include month-of-origination fixed effects. Robust standard errors are clustered by origination month. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

behavioral channels. We implement this idea by estimating the following model on the pooled 2017–2018 data:

$$Default_i = \beta_1 PostCash_i + \beta_2 PostDirect_i + X_i\gamma + \mu_t + \epsilon_i, \tag{9}$$

where $PostCash_i$ and $PostDirect_i$ are indicators for 2018 cash and 2018 direct-pay loans, respectively, and 2017 cash loans serve as the omitted baseline.

Our identification strategy exploits this contract-choice environment rather than treating self-selection as a nuisance. The key idea is that the introduction of the direct-pay option transforms an unobserved borrower attribute—the private cost of default and associated self-control problem—into an observable signal through the endogenous choice between cash and direct-pay. Under the separating logic in Proposition 2, this contract choice is monotone in type: high-cost, sophisticated borrowers are more likely to select the commitment device, while low-cost borrowers favor cash liquidity. This specification uses the pre-policy cohort to pin down the baseline mixture of types, and the post-policy sorting across contracts to infer how much of adopters' superior performance reflects a change in composition (selection) versus a genuine reduction in default risk for a given type (behavioral commitment), without relying on external instruments for adoption. Under the maintained separation assumption, comparing the observed default rate of 2018 direct-pay adopters to their inferred counterfactual default rate had they remained in the cash regime yields a treatment-on-the-treated (TOT) effect of actually adopting the commitment device on adopters' default risk.

Before proceeding, we must validate the key assumption that the aggregate pool of eligible borrowers remained stable between 2017 and 2018. The underlying distribution of unobserved risk types cannot be tested directly, but we can examine whether the composition of observable borrower and loan characteristics changed around the policy introduction. To this end, we conduct a covariate balance test reported in Appendix A.2. Table A10 compares the characteristics of eligible borrowers from 2017 and 2018 and finds only small, statistically insignificant differences across income, credit scores, debt burdens, and other observables. While this does not rule out shifts in unobservables, the stability of observables supports the maintained assumption that the borrower pool did not materially change, so that observed differences in default outcomes are most plausibly attributed to the policy's sorting and behavioral effects rather than to an exogenous shift in borrower quality.

Table Table 5b reports these results. These estimates strongly validate the adverse selection mechanism predicted by our theoretical framework. The coefficient on $PostCash$ is positive and significant at around 0.010. This indicates that the 2018 cash-only pool performed significantly worse than the 2017 baseline, even after controlling for observables. Because the DiD estimate yields an underlying time trend of about 0.8 percentage points, the cash borrowers are performing worse by about 0.2 percentage points. Because cash borrowers face the same course of actions after policy introduction, any deterioration is most likely driven by composition of underlying borrower risk. This deterioration confirms that creditworthy high-type borrowers have migrated to the new direct-pay option, leaving a riskier low-type pool behind. This is precisely the sorting predicted by our contract design and self-selection theory. The Cox proportional-hazard estimates in Table A12 in Appendix A.3 provide complementary evidence, showing that direct-pay borrowers face substantially lower default hazards than comparable cash borrowers.

Having accounted for selection, the behavioral effect is revealed in the $PostDirect$ coefficient. This coefficient is -0.023, indicating that adopters defaulted 2.3 percentage points below the 2017 baseline. This substantial improvement, which goes far beyond what can be explained by sorting, is attributable to the behavioral commitment effect. By locking in their ex-ante intention, the device prevents the ex-post misuse of funds and directly improves repayment outcomes. We now outline the decomposition of these two effects more explicitly.

**Decomposition.** Figure 2 visualizes this decomposition, separating the total policy effect into its selection and behavioral components. All figures are group means without adjusting for borrower characteristics. The 2018 data reveals a 3.6 percentage point gap in default rates between cash borrowers (6.2%) and direct-pay adopters (2.6%). Our identification relies on an assumption from our theoretical model: the 2018 choice induces perfect separation, where all cash borrowers are low-types ($c < \bar{c}$) and all direct-pay adopters are high-types ($c \geq \bar{c}$). We use this assumption to conduct a back-of-the-envelope calculation.

*First*, we establish the 2017 baseline for low-types. From our DiD model in Equation (7), we estimate a 0.8 percentage point market-wide upward trend in defaults from 2017 to 2018. Adjusting for this trend, the counterfactual 2017 default rate for low-types was 5.4%.

*Second*, we calculate the selection effect by backing out the high-types' 2017 default rate. Given the 2017 aggregate rate of 5.2% and using the 2018 adoption share of 24% as the proportion of high-types, the high-types' 2017 default rate must have been 4.5%.[16] This reveals the pure selection effect: a 0.9 percentage point baseline difference in creditworthiness between low-types (5.4%) and high-types (4.5%).

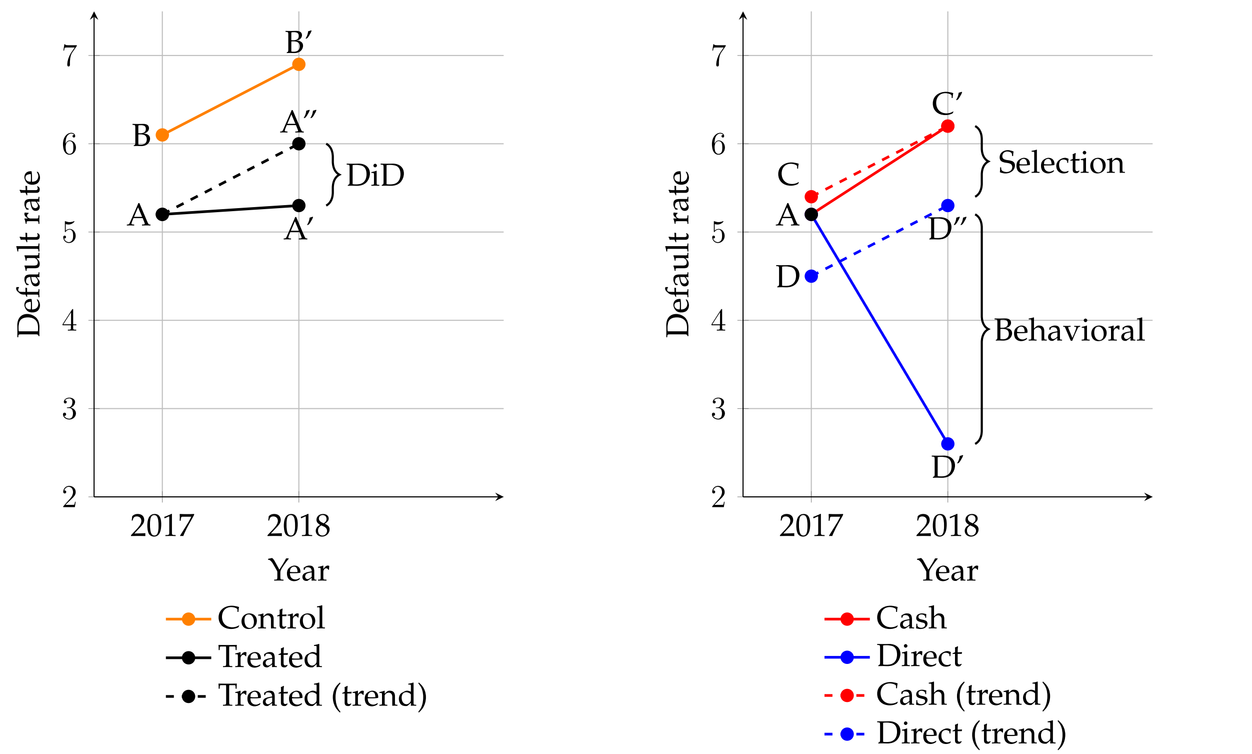
*Last*, we calculate the behavioral effect. A high-type borrower in 2018, absent the commitment device, should have defaulted at 5.3% (their 4.5% baseline plus the 0.8% trend). Direct-pay adopters reduce their default rates by approximately 2.7 percentage points (roughly 51%) relative to what they would have defaulted at absent the commitment device, demonstrating the substantial behavioral improvement achieved by the commitment device. This 2.7 percentage point decline represents our estimated treatment-on-

[16] The calculation is: $5.2\% = (0.76 \times 5.4\%) + (0.24 \times \text{Default}_{H,2017})$, which yields $\text{Default}_{H,2017} \approx 4.5\%$.

Figure 2: Default Rate Dynamics and Decomposition

(a) Policy Effect: Eligible (Treated) vs. Ineligible (Control) Loans

(b) Decomposition: Cash vs. Direct-Pay Defaults (Eligible Loans Only)




*Notes:* This figure plots average one-year default rates for various groups of borrowers in 2017 (pre-policy) and 2018 (post-policy). All values are group means without adjusting for borrower characteristics.

Panel (a) shows the effect of policy availability from the DiD analysis in Section 4.2, specifically Table 3 column (1). The treated group consists of debt-refinancing loans eligible for the direct-pay option (points A in 2017 and A′ in 2018). The control group consists of consumption loans ineligible for the option (points B in 2017 and B′ in 2018). Point A″ is the counterfactual default rate of the treated group in 2018 under the parallel trends assumption. The policy effect is given by the difference between A and A″.

Panel (b) decomposes the policy effect for eligible borrowers (debt-refinancing loans) by their actual disbursement choice, based on Table 5b column (1). *Observed default rates:* Point A is all eligible borrowers in 2017; point C′ is cash borrowers in 2018; point D′ is direct-pay borrowers in 2018. *Counterfactual default rates:* Point C is the counterfactual default rate of cash borrowers in 2017 under the parallel trends assumption; point D is the counterfactual default rate of direct-pay borrowers in 2017, obtained by decomposing A into the two groups C and D; point D″ is the counterfactual default rate of direct-pay borrowers in 2018 under selection but no behavioral effect, i.e., point D plus the time trend. The selection effect is given by the difference between C and D, and the behavioral effect is given by the difference between D′ and D″.

the-treated effect of direct-pay adoption on default among adopters, net of selection. Of the 3.6 percentage point gap between cash and direct-pay borrowers in 2018, approximately three-quarters (2.7 percentage points) is attributable to behavioral improvement, while one-quarter (0.9 percentage points) is attributable to selection.

# 5 Structural Model and Estimation

We next develop and estimate a structural model to interpret the mechanisms underlying our reduced-form findings (Aguirregabiria and Mira 2010). The empirical patterns suggest that the direct-pay feature both attracts borrowers with stronger repayment discipline and improves repayment behavior through a commitment effect. To quantify the relative importance of these channels and to evaluate alternative policy designs, we require a framework that links observed choices and default outcomes to the latent primitives that drive them. The structural model provides this link: it embeds borrowers' repayment and consumption decisions in a dynamic discrete-choice environment, allowing us to recover unobserved heterogeneity in default costs and self-control, separate selection from behavioral commitment, and conduct counterfactual exercises that cannot be implemented with reduced-form methods alone. This approach follows the literature of using dynamic structural estimation in finance to uncover economic primitives and evaluate policy or institutional frictions, such as Hennessy and Whited 2005; Hennessy and Whited 2007 on financing and bankruptcy costs, Strebulaev 2007 on dynamic capital structure, and Morellec, Nikolov, and Schürhoff 2012 on governance frictions. We introduce the framework to the context of household finance (e.g., Vihriälä 2023) and apply the model to study intertemporal self-control and commitment.

## 5.1 Model and Specification

The model has three main features. First, we allow for variation among borrowers in their underlying unobserved creditworthiness, which we interpret as the default cost. Borrowers' unobserved types influence their optimal choices for the disbursement method and their repayment behavior. Second, we explicitly account for the tradeoff borrowers face between the direct-pay and cash options. If the borrower selects the cash option, he enjoys an immediate gratification by spending a proportion of the loan amount, leading to an increased future repayment burden. In contrast, the direct-pay option compels borrowers to adhere to their original plan, maintaining a smaller debt burden. Third, we model the borrowers' monthly repayment behavior using a dynamic discrete choice model. The disbursement method affects the total debt burden once the loan originates, and the default cost affects borrowers' incentives to repay their loan.

Let $X$ denote the set of borrower and loan characteristics, such as loan size, annual income, credit score (FICO), debt-to-income ratio, and the length of credit history. We model default cost as a binary type $c \in \{c_H, c_L\}$ to align with our theoretical framework, where separation occurs at a threshold $\bar{c}$ that divides borrowers into two groups. This binary structure captures the essential heterogeneity needed to identify the selection and behavioral effects.The distribution of the default cost $c$ depends on characteristics $X$ and is parameterized by the logistic function,

$$P(H) = \frac{\exp(X\theta_p)}{1 + \exp(X\theta_p)}. \tag{10}$$

The borrower has an existing debt of size $s$ and approaches the lending platform to refinance this debt. He requests a loan of equal size $s$ and term $T = 36$. The platform offers two disbursement options, either cash or direct-pay, each with different interest rates. The cash disbursement deposits the loaned amount $s$ to the borrower's account upon approval with the interest rate $r_c$. Once the loan originates, the borrower uses some proportion $\alpha \in [0, 1]$ of the loan for immediate consumption and the platform has no control over this behavior. Their debt burden increases to $(1 + \alpha)s$. The direct-pay option, on the other hand, forwards the loan amount directly to the borrower's existing creditors. The borrower does not receive cash and needs to repay the loan with the interest rate $r_d$. The platform determines the interest rates of the loans based on the borrowers' observable characteristics and the disbursement methods they choose. The platform's interest rate algorithm is considered exogenous in our model and can be estimated from the data. Once the loan originates, the borrower makes monthly repayment decisions until either default or the end of the loan term $T$. The borrower's strategy includes choosing between cash and direct-pay disbursement options $DP \in \{0, 1\}$, and making repayment decisions $a_t \in \{0, 1\}$ after the loan is originated for $t = 1, \cdots, T$.

To capture heterogeneity in borrowers' propensity to consume, we allow the parameter $\alpha$ to depend on borrowers' observable characteristics with the following specification,

$$\alpha = \frac{\exp(X\theta_\alpha)}{1 + \exp(X\theta_\alpha)}. \tag{11}$$

**Repayment decisions.** The repayment decisions follow the models of Kawai, Onishi, and Uetake 2022 and Xin 2025. Once the loan originates, the borrower makes a binary repayment decision $a_t$ at $t = 1, 2, \cdots, T$. The borrower chooses to either repay a fixed monthly installment $m$ ($a_t = 0$) or default ($a_t = 1$). The size of the monthly installment $m$ is determined by the loan size $s$, term $T$, and interest rate $r$.[17] In addition to making the monthly payment $m$, we specify that the borrower's repayment utility consists of an

[17]The fixed monthly installment $m$ is given by $s\left[\frac{r(1+r)^T}{(1+r)^T - 1}\right]$. The outstanding balance in period $t$, given that the borrower has paid the monthly installments up to period $t - 1$, is $B_t = s\left[\frac{(1+r)^{T+1} - (1+r)^t}{(1+r)^T - 1}\right]$.

additive month-specific term $k_t$ following Kawai, Onishi, and Uetake 2022.

The utilities of the two actions at $t < T$ are given by:

$$\begin{cases} u(-m) + \delta V_{t+1}(s, r, c) + \epsilon_{t,0} & \text{for paying installment,} \\ u(-c) + \epsilon_{t,1} & \text{for default,} \end{cases} \tag{12}$$

where $\epsilon_t = (\epsilon_{t,0}, \epsilon_{t,1})$ are the idiosyncratic utility shocks associated with each alternative and are assumed to be i.i.d. and to follow the type I extreme value distribution with a scale parameter $\sigma_\epsilon$. We allow $\sigma_\epsilon$ to be different for the cash and direct-pay options and denote them $\sigma_{\epsilon,\text{cash}}$ and $\sigma_{\epsilon,\text{direct}}$. $\delta$ is the discount factor. $V_{t+1}(s, r, c)$ is the ex-ante expected continuation value at the beginning of period $t + 1$ if the borrower chooses to repay an installment at $t$. Specifically,

$$V_{t+1}(s, r, c) = \mathbb{E}\Bigg( \max \Big\{ u(-m) + \delta V_{t+2}(s, r, c) + \epsilon_{t+1,0}, u(-c) + \epsilon_{t+1,1} \Big\} \Bigg). \tag{13}$$

In the last repayment period $T$, the continuation value of the loan is zero, so the borrowers utility for the two options is

$$\begin{cases} u(-m) + \epsilon_{T,0} & \text{for paying installment,} \\ u(-c) + \epsilon_{T,1} & \text{for default.} \end{cases} \tag{14}$$

By backward induction, we can derive the ex-ante value of a loan before the borrowers make any repayments $V_1(s, r, c)$. This value is important for the borrowers' choices of disbursement method, as we will explain below.[18]

**Choice of disbursement method.** When choosing the disbursement method, the borrower takes into account the value of the loan at the repayment stage and their immediate gratification. If the borrower chooses the direct-pay option, he faces a loan of size $s$ at the interest rate $r_d$. So, the value of the loan is $V_1(s, r_d, c)$. For those who choose the cash option, they receive a cash amount of $s$ at the interest rate $r_c$. After receiving the cash, the borrower uses a certain proportion $\alpha \in [0, 1]$ for immediate discretionary spending and enjoys the utility of spending $\alpha s$ and a fixed benefit of choosing the cash option $\omega$. We interpret $\omega$ as the preference for flexibility and allow $\omega$ to vary across the type of borrowers and denote them $\omega_H$ and $\omega_L$. Because of the spending, the borrower now has a larger

[18] Note also that $V_1(s, r, c)$ satisfies the submodularity condition in the theoretical framework. See Appendix A.1 for the explanation.

debt burden of $(1+\alpha)s$ to pay later. The expected utility of choosing the two kinds of disbursement methods is given by

$$\begin{cases} u(\alpha s+\omega)+V_1((1+\alpha)s,r_c,c)+\eta_0 & \text{for cash,} \\ V_1(s,r_d,c)+\eta_1 & \text{for direct-pay,} \end{cases} \tag{15}$$

where $\eta=(\eta_0,\eta_1)$ is the random utility shocks associated with either option. We similarly let $\eta$ follow the type I extreme value distribution with scale parameter $\sigma_\eta$.

**Connecting the structural and theoretical models.** A key feature of our structural estimation is the use of the propensity to consume, $\alpha$, to capture the severity of the self-control problem, rather than directly estimating the present-bias parameter, $\beta$. This modeling choice is deliberate and rests on two justifications.

First, $\beta$ is not separately identified in our data. A clean estimation of $\beta$ would require observing the same individual's conflicting choices between immediate and delayed rewards, typically under ex-ante and ex-post conditions, as is common in other field or experimental settings (Fang and Silverman 2009; Fang and Wang 2015; Augenblick and Rabin 2019; Martinez, Meier, and Sprenger 2023; Laibson et al. 2024). Our observational data, however, only reveal the outcome of this internal conflict (i.e., the choice of contract and subsequent default), not the preference reversal itself.

Second, and more importantly, $\alpha$ serves as the "reduced-form" behavioral consequence of the "deep" preference parameter $\beta$. While we treated $\alpha$ as exogenous in our simplified theoretical model (Section 3), it can be micro-founded as an endogenous choice variable of the agent. In Equation (4), the "doer" self at $t=1$ chooses an optimal $\alpha^*$ to maximize $U_1^{\text{spend}}$. This optimal $\alpha^*$ is a direct function of $\beta$.

**Proposition 3.** *Assuming $u$ and $V_1$ are concave in $s$, the optimal propensity to consume, $\alpha^*$, is decreasing in $\beta$, i.e., $\frac{\partial\alpha^*}{\partial\beta}<0$.*

The intuition is straightforward: as a borrower becomes more present-biased (a lower $\beta$), they discount the future negative consequences of debt more heavily. This lowers the perceived marginal cost of spending, leading them to choose a larger $\alpha^*$. Therefore, $\alpha$ and $\beta$ are inversely related. In our data, these parameters are observationally equivalent, and $\alpha$ is the channel through which self-control problems manifest as default risk. Estimating the reduced-form parameter $\alpha$ is therefore sufficient, as it endogenously captures the full behavioral impact of the unobserved deep preference parameter $\beta$.

## 5.2 Estimation

We estimate the structural parameters of the model using the Generalized Method of Moments (GMM). The estimation is performed on the subsample of 3-year loans to maintain consistency with the model's fixed term structure ($T = 36$ months). The vector of parameters to be estimated includes the default costs ($c_H, c_L$), the borrower type distribution ($\theta_p$), the propensity for discretionary consumption ($\theta_\alpha$), the type-specific preferences for cash ($\omega_H, \omega_L$), and the scale parameters for the idiosyncratic utility shocks ($\sigma_\eta, \sigma_{\epsilon,\text{cash}}, \sigma_{\epsilon,\text{direct}}$). The GMM estimator identifies these parameters by minimizing the weighted quadratic distance between a set of empirical moments from the data and the corresponding moments simulated from the model.

The model is identified by matching key moments that capture the central features of the data and the policy's impact, as shown in the model fit results in Appendix A.5. Specifically, we target four main moments: (1) the average one-year default rate in the 2017 pre-policy cohort; (2) the probability of choosing the direct-pay option in the 2018 post-policy cohort; (3) the one-year default rate for cash borrowers in 2018; and (4) the one-year default rate for direct-pay borrowers in 2018. These moments are chosen precisely because they encapsulate the selection and behavioral effects of the policy introduction.

**Identification of parameters.** Identification of the model's parameters relies on how these moments jointly discipline the structural mechanisms. The default cost parameters ($c_L$, $c_H$) are primarily identified by the level of default rates (Moments 1, 3, and 4). The dynamic repay-vs-default decision in Equation (12) is a trade-off between the installment payment and the default cost, so the observed default probabilities pin down the average magnitude of this cost.

The parameters governing selection, the type distribution $P(H)$ and the cash preferences ($\omega_L$, $\omega_H$), are identified by the disbursement choice (Moment 2). The 25.9% take-up rate of the direct-pay option reveals the proportion of borrowers for whom the commitment value and interest rate discount outweigh the preference for cash liquidity ($\omega$). Variation in this choice across observable characteristics helps separate the type probability $P(H)$ from the cash preference $\omega$.

Finally, the key self-control parameter, $\alpha$, is identified by the difference in default rates between the cash and direct-pay paths, after accounting for the selection effect. The 2017 default rate (Moment 1) provides a pre-policy baseline. In 2018, cash borrowers (Moment 3) default at a high rate (5.8%), while direct-pay borrowers (Moment 4) default at a much lower rate (2.6%). This 3.2 percentage point gap is driven by two factors: (1) sorting of

Table 6: Parameter Estimates of the Structural Model

| Parameter | Estimate | SE |
|---|---|---|
| $c_L$ | $2.721^{***}$ | (0.000) |
| $c_H$ | $4.539^{***}$ | (0.000) |
| $P(H)$ | $0.688^{***}$ | (0.002) |
| $\alpha$ | $0.344^{***}$ | (0.001) |
| $\omega_L$ | $0.374^{***}$ | (0.012) |
| $\omega_H$ | $0.743^{***}$ | (0.014) |
| $\sigma_\eta$ | $0.463^{***}$ | (0.006) |
| $\sigma_{\epsilon,\text{direct}}$ | $0.190^{***}$ | (0.008) |
| $\sigma_{\epsilon,\text{cash}}$ | $0.141^{***}$ | (0.031) |

*Notes:* This table reports the parameter estimates and average fitted values from the structural model in Section 5.1. $c_L$ and $c_H$ are the fixed default costs for low- and high-type borrowers, respectively. $P(H)$ and $\alpha$ are the average fitted values for the probability of being a high-type borrower (Equation (10)) and the propensity to consume (Equation (11)), respectively. $\omega_L$ and $\omega_H$ represent the non-pecuniary utility (preference for flexibility) of the cash option for low- and high-types (Equation (15)). $\sigma_\eta$ is the scale parameter for the disbursement choice utility shock (Equation (15)). $\sigma_{\epsilon,\text{direct}}$ and $\sigma_{\epsilon,\text{cash}}$ are the scale parameters for the dynamic repayment (pay vs. default) utility shocks for borrowers in the direct-pay and cash paths, respectively (Equation (12)). Standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

high-types into direct-pay and (2) the behavioral commitment effect. The model attributes the portion of this gap not explained by selection to the fact that cash borrowers' debt burden increases to $(1+\alpha)s$, while direct-pay borrowers' burden remains $s$. The magnitude of $\alpha$ is thus pinned down by the excess default risk observed among cash borrowers.

## 5.3 Estimation Results

Table 6 presents the parameter estimates for the structural model, with the corresponding estimates for borrower heterogeneity (covariate effects) detailed in Table 7. Model fit is presented in Table A13 in Appendix A.5.

The first set of parameters provides the intercept terms for the model's core components. Based on our estimates, the default cost for low-type borrowers ($c_L$) is $2.721$, while the default cost for high-type borrowers ($c_H$) is $4.539$. The probability of being a high-type borrower varies with observable characteristics: as shown in Table 7, borrowers with higher annual income, higher FICO scores, lower debt-to-income ratios, and longer credit histories are significantly more likely to be the high-type. On average, 68.8% of the borrowers in our sample are estimated to be the high-type.

Table 7: Covariate Effects on Type Distribution ($P(H)$), Consumption ($\alpha$), and Marginal Probabilities

| | $P(H)$ | | | $\alpha$ | | | $P$(Direct) | $P$(Default) |
|---|---|---|---|---|---|---|---|---|
| | Est | SE | ME | Est | SE | ME | ME | ME |
| Loan amount | $1.036^{***}$ | (0.014) | 0.185 | $-0.928^{***}$ | (0.019) | -0.179 | -0.035 | -0.018 |
| Log annual income | $0.302^{***}$ | (0.007) | 0.054 | $-0.228^{***}$ | (0.008) | -0.044 | -0.011 | -0.007 |
| FICO score | $0.038^{***}$ | (0.007) | 0.007 | $-0.013$ | (0.013) | -0.002 | -0.001 | -0.001 |
| Debt-to-income ratio | $0.109^{***}$ | (0.000) | 0.020 | $-0.049^{***}$ | (0.003) | -0.009 | -0.004 | -0.002 |
| Own home (indicator) | $0.018^{***}$ | (0.003) | 0.003 | $0.004^{**}$ | (0.002) | 0.001 | -0.000 | -0.000 |
| Credit history length | $0.028^{***}$ | (0.009) | 0.005 | $-0.047^{***}$ | (0.005) | -0.009 | -0.002 | -0.001 |
| Inquiries last 6 months | $-0.052^{***}$ | (0.007) | -0.009 | $-0.005$ | (0.014) | -0.001 | 0.001 | 0.001 |
| Open accounts | $0.092^{***}$ | (0.004) | 0.017 | $-0.073^{***}$ | (0.000) | -0.014 | -0.004 | -0.003 |
| Revolving utilization | $0.102^{***}$ | (0.008) | 0.018 | $-0.087^{***}$ | (0.007) | -0.017 | -0.004 | -0.003 |
| Intercept | $1.086^{***}$ | (0.009) | 0.194 | $-0.852^{***}$ | (0.003) | -0.164 | -0.000 | -0.000 |

*Notes:* This table reports the coefficient estimates for the heterogeneity in the structural model. The table reports the coefficients ($\theta_p$, $\theta_\alpha$) showing the effect of observables on the probability of being a high-type, $P(H)$ (Equation (10)), and on the propensity to consume, $\alpha$ (Equation (11)). The "ME" columns report the marginal effects of each characteristic on the simulated probability of choosing the direct-pay option and the overall probability of default. "Est" denotes estimates, "SE" denotes standard errors, and "ME" denotes marginal effects. Standard errors are computed using GMM. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

We also find that the average propensity to consume, $\alpha$, is 0.344. This suggests that, on average, borrowers spend approximately 34.4% of the cash loan on discretionary consumption. Table 7 indicates that borrowers with higher annual incomes and longer credit histories tend to spend a smaller proportion of their loans. Interestingly, borrowers with higher debt-to-income ratios also exhibit less discretionary spending, perhaps reflecting a stronger incentive to avoid wasteful spending given their precarious financial state.

The subsequent parameters in Table 6 shed light on the non-pecuniary drivers of selection and repayment. The estimates for $\omega_L$ and $\omega_H$ quantify the utility of liquidity and flexibility, the "cash preference", for low- and high-type borrowers, respectively. We find this preference is positive and highly significant for both types but substantially larger for high-type borrowers ($\hat{\omega}_H = 0.743$) compared to low-type borrowers ($\hat{\omega}_L = 0.374$). Despite this higher cash preference, high-type borrowers are still more likely to choose the direct-pay option because their higher default costs ($c_H > c_L$) make the commitment value of direct-pay more valuable relative to the foregone cash utility. This difference in default costs relative to cash preferences helps drive the separating equilibrium, as the direct-pay option provides a net benefit for high-type borrowers that outweighs their stronger preference for cash.

**Borrower heterogeneity.** Table 7 outlines the determinants of the borrower's type and their propensity for discretionary consumption. The probability of being a high-type, $P(H)$, is positively associated with standard measures of financial stability and creditworthiness, such as higher loan amounts, higher log annual income, higher FICO score, lower debt-to-income ratio, homeownership, longer credit history, more open accounts, and higher revolving utilization. This aligns with the interpretation of the high-type as being more creditworthy and reliable. The model also shows that the propensity for discretionary spending ($\alpha$), which captures self-control problems, is significantly lower for borrowers with higher loan amounts, higher incomes, higher DTI, longer credit histories, more open accounts, and higher revolving utilization. This suggests that both financial discipline (income, history) and financial constraints (DTI, loan amount) can reduce impulsive spending. Homeownership is associated with a slightly higher propensity to consume, perhaps reflecting reduced liquidity constraints.

Finally, the marginal effects (ME) in Table 7 reveal the net impact of these characteristics on the two key outcomes: disbursement choice and default probability. We find that larger loan amounts are associated with lower direct-pay adoption (ME = -0.035), while characteristics like income, FICO, and credit history have smaller negative effects. The marginal effects on the overall probability of default, $P$(default), synthesize these competing channels. Consistent with standard intuition, higher income, higher FICO scores, longer credit history, lower DTI, more open accounts, and lower revolving utilization are all associated with a lower default probability. These results are driven by the structural channels we've identified: borrowers with better financial characteristics are more likely to be high-types (higher $P(H)$) and have lower propensities to consume (lower $\alpha$), both of which reduce default risk.

## 5.4 Simulations: Decomposition and Other Policy Designs

With the estimated parameters, we now conduct counterfactual simulations to decompose the policy's effects and evaluate alternative policy designs. We simulate borrower choices and repayment decisions under several scenarios, with the results presented in Table 8.

**Self-control problems.** The results in Table 8, Panel A, quantify the role of self-control problems in driving default. The "rational benchmark" scenario (row 1) shows that without self-control problems ($\alpha = 0$), the market's default rate would be 3.5%. The "behavioral baseline" scenario (row 2) shows that introducing self-control problems ($\alpha > 0$)

Table 8: Simulation Results: Decomposition and Policy Designs

| Scenario | Take-up rate | Default rate | | |
|---|---|---|---|---|
| | | Cash | Direct-pay | Overall |
| **Panel A: Self-control problems** | | | | |
| (1) Rational benchmark ($\alpha = 0$) | - | 3.5% | - | 3.5% |
| (2) Behavioral baseline (pre-intervention) | - | 5.7% | - | 5.7% |
| **Panel B: Policy effects and decomposition** | | | | |
| (3) Zero-discount policy (direct-pay but no discount) | 23.1% | 6.0% | 3.8% | 5.4% |
| (4) Current policy (direct-pay & discount) | 26.1% | 5.8% | 2.6% | 5.0% |
| (5) Selection only (no behavioral improvement) | 26.1% | 5.8% | 5.4% | 5.7% |
| **Panel C: Counterfactual policy simulations** | | | | |
| (6) Mandatory direct-pay (100% take-up) | 100.0% | - | 3.4% | 3.4% |
| (7) Reduced adoption friction ($\omega$ down by 10%) | 28.7% | 5.9% | 2.7% | 4.9% |
| (8) Reduced discretionary spending ($\alpha$ down by 10%) | 28.4% | 5.6% | 2.7% | 4.8% |

*Notes:* This table reports the simulated one-year default rates from the estimated structural model under various counterfactual scenarios. "Take-up rate" reports the percentage of borrowers who choose the direct-pay option in that scenario. "Default rate," which is split into "cash," "direct-Pay," and "overall," reports the average one-year default rates for the respective groups. Panel A compares scenarios with and without self-control problems. Panel B decomposes the policy effects by comparing scenarios with different policy features. Panel C evaluates alternative policy designs. The scenarios are defined as:
(1) Rational benchmark: Assumes no self-control problems ($\alpha = 0$ for all borrowers) and only the cash disbursement option is available.
(2) Behavioral baseline: Uses the estimated $\alpha$ and assumes only the cash disbursement option is available, corresponding to the 2017 market.
(3) Zero-discount policy: Introduces the direct-pay option but sets the interest rate discount to zero for all borrowers.
(4) Current policy: Simulates the observed policy using estimated parameters and the observed interest rate discounts from the 2018 data.
(5) Selection only: Simulates selection effects only, with no behavioral improvement. Borrowers are sorted into disbursement options as under the current policy regime (scenario 4), but default rates are held at pre-policy levels.
(6) Mandatory direct-pay: A mandatory policy where all borrowers are forced to use the direct-pay option.
(7) Reduced adoption friction: Simulates the current policy, but borrowers' preference for cash, $\omega$, is reduced by 10% to model a reduction in non-price adoption frictions.
(8) Reduced discretionary spending: Simulates the current policy, but borrowers' propensity to spend, $\alpha$, is reduced by 10% to model a reduced propensity to consume.

increases the default rate to 5.7%. This 2.2 percentage point increase implies that self-control issues account for approximately 39% of all defaults in the pre-policy market.

**Policy effects and decomposition.** We next decompose the policy's effects to understand the separate roles of commitment and price incentives. We simulate three scenarios: a "zero-discount policy" that introduces the direct-pay option but offers no interest rate discount (row 3); the "current policy" with the observed discounts (row 4); and a "selection only" scenario that simulates selection effects but no behavioral improvement (row 5).

The results in Table 8, Panel B, reveal the importance of both commitment and price incentives. The zero-discount policy (row 3) shows that introducing the direct-pay option without a discount improves the overall default rate from 5.7% to 5.4%. About 23.1% of borrowers adopt the option and achieve a default rate of 3.8%, demonstrating substantial behavioral improvement even without price incentives. However, this policy adversely selects the remaining cash pool, whose default rate rises to 6.0%.

The current policy (row 4) shows that the interest rate discount plays a nontrivial role: by increasing take-up to 26.1%, an additional 3.0 percentage point from the zero-discount policy, the discount attracts enough borrowers to overcome the selection effect and successfully lowers the overall market default rate to 5.0%.[19]

The selection only scenario (row 5) simulates what would happen if borrowers chose the direct-pay option as they do under the current policy, but without any behavioral improvement. As expected, the overall default rate remains at 5.7%, the same level as the behavioral baseline. This counterfactual isolates the behavioral improvement: under the current policy, direct-pay adopters reduce their default rates from 5.4% in the absence of behavioral improvement to 2.6% with the commitment device, an approximately 2.8 percentage point (52%) reduction, demonstrating the substantial behavioral improvement generated by the policy. The cash borrowers default at 5.8% and the direct-pay borrowers default at 5.4%. This leaves a gap of 0.4 percentage points that is attributed to the selection effect. Of the 3.2 percentage point gap between cash and direct-pay borrowers under the current policy, approximately 87% (2.8 percentage points) is attributable to behavioral improvement, while 13% (0.4 percentage points) is attributable to selection.

The estimates are broadly consistent with our reduced-form decomposition in Section 4.4, where we found that direct-pay adopters reduce their default rates by approximately 2.7 percentage points (roughly 51%) relative to their counterfactual default rate absent the commitment device, and where the 3.6 percentage point gap between cash and direct-pay borrowers is decomposed into approximately three-quarters behavioral improvement and one-quarter selection. The difference in magnitudes is expected given that the structural model is estimated on the subsample of 3-year loans, while the reduced-form analysis uses the full sample including both 3- and 5-year loans. The fact that both approaches yield similar estimates of the behavioral improvement, with direct-pay

[19]Observe that the cash borrowers also see a decrease in default rate from 6.0% to 5.8%, indicating that the quality of the cash pool has improved compared to the zero-discount policy. This is primarily driven by the interest rate discount, which is, at the time of policy implementation, offered to more risky borrowers.

adopters reducing their default rates by approximately half relative to their counterfactual default rate absent the commitment device, reinforces the validity of our findings and demonstrates that the behavioral commitment effect is the primary driver of the policy's success.

**Other policy designs.** We now consider several stylized counterfactual policies to evaluate alternative designs. The simulation results are presented in Table 8, Panel C. Before proceeding, we remind readers that these simulations are stylized and should be interpreted with caution.

First, we simulate a "mandatory direct-pay" policy where all borrowers are required to take the direct-pay option. This simulates a full intervention. Because borrowers declare they are borrowing to restructure debt, this policy could help filter out those who may misrepresent their loan's purpose. Row (6) shows that this policy reduces the overall default rate to 3.4%, a 1.6 percentage point improvement over the current policy's 5.0%. A clear drawback is inflexibility, which might drive away borrowers with strong liquidity preferences. A more realistic implementation might require a minimum percentage of the loan to be direct-pay, which would place the default rate between 3.4% and 5.0%.

Second, we simulate a "reduced adoption friction" policy. Given the significant friction $\omega$ (cash preference) that deters adoption, a lender could design a policy to make this choice less costly, for example, by offering a liquidity guarantee. While it is difficult to assess the true magnitude of this effect, we simulate a hypothetical scenario in row (7) that reduces the friction $\omega$ by 10%. We find that take-up increases to 28.7% and the overall default rate falls to 4.9%, a 0.1 percentage point improvement over the current policy.

Third, we simulate a "reduced discretionary spending" scenario by assuming borrowers use a 10% smaller proportion $\alpha$ of the loan for discretionary consumption. In our model, $\alpha$ captures the share of the loan that the $t = 1$ "doer" self diverts to immediate consumption instead of debt repayment, so a lower $\alpha$ corresponds to policies that limit the scope for impulsive spending, such as faster disbursement that shortens the gap between approval and funding (keeping the borrower closer to the $t = 0$ "planner" state), staggered or installment disbursement of the cash portion rather than a lump-sum payout, or routing the funds through a controlled spending channel (e.g., a card or account that restricts high-temptation categories). These interventions effectively reduce the amount of cash that is freely available at the moment of temptation. In this conservative scenario (row 8), reducing $\alpha$ by 10% lowers the overall default rate to 4.8%, a 0.2 percentage point improvement relative to the current policy.

# 6 Conclusion

This paper provides novel field evidence that self-control problems are significant and costly frictions in consumer credit markets, distinct from traditional models of asymmetric information. We analyze the introduction of a "direct-pay" disbursement option by a large peer-to-peer lender, a policy innovation that functions as both a commitment device for behavioral frictions and a screening mechanism for informational frictions. Our contribution is to integrate these two frameworks theoretically and empirically, developing and estimating a structural model that simultaneously features unobserved borrower heterogeneity and self-control problems, allowing us to separately quantify the selection and behavioral channels that drive the policy's effectiveness.

Our theoretical framework, based on time-inconsistent preferences, shows that sophisticated, present-biased borrowers have an ex-ante incentive to adopt commitment to constrain their ex-post selves from misusing funds. The model also demonstrates how the direct-pay option induces a separating equilibrium: high-cost borrowers (who intend to repay but face self-control problems) self-select into the commitment device, while low-cost borrowers (who are prone to default) prefer cash for its liquidity. This dual role, as both a behavioral intervention and an informational innovation, creates an alignment of incentives between borrowers and lenders, distinguishing it from standard screening models where gains are often zero-sum.

Our empirical analysis confirms the policy's effectiveness and disentangles its dual effects. Using a difference-in-differences design, we show that the availability of the direct-pay option significantly reduces default rates for eligible borrowers by approximately 0.6 percentage points (an 11% decline relative to the pre-policy mean). Most importantly, our decomposition analysis reveals the substantial behavioral improvement achieved by direct-pay adopters. We find that direct-pay adopters reduce their default rates by approximately 2.7 percentage points (roughly 51%) relative to their counterfactual default rate absent the commitment device. Of the gap between cash and direct-pay borrowers in 2018, approximately three-quarters is attributable to behavioral improvement, while one-quarter is attributable to selection.

To quantify these mechanisms and evaluate counterfactuals, we develop and estimate a dynamic structural model of borrower choice and repayment. Our estimates reveal that self-control problems are a significant driver of default: they account for approximately 39% of all defaults in the pre-policy market. The model estimates that borrowers spend, on average, 34.4% of cash loan proceeds on discretionary consumption, and that 68.8% of borrowers are high-types who benefit from commitment. Counterfactual simulations show that a zero-discount policy improves aggregate outcomes from 5.7% to 5.4%, while the current policy's interest rate discount achieves a larger reduction to 5.0%. A mandatory direct-pay policy could further reduce defaults to 3.4%, but at the cost of borrower flexibility.

Our findings demonstrate a crucial insight: self-control problems harm both borrowers and lenders, creating an opportunity for "win-win" contract design that improves borrower welfare while enhancing lender profitability. This paper shows that financial contracts can be powerful tools to address behavioral biases, suggesting that financial innovation aimed at mitigating self-control can enhance market efficiency and promote responsible borrowing behavior. The integration of behavioral frameworks with asymmetric information, both theoretically and empirically, opens new avenues for understanding and designing credit contracts that address the complex frictions present in modern consumer finance markets.

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# Appendix A

## A.1 Model Details

**Proof of Proposition 1.** Let $\Delta V_1 = V_1^{\text{abstain}} - V_1^{\text{spend}}$ be the net continuation value lost from discretionary spending.

The $t = 0$ "planner" self prefers to abstain if $U_0^{\text{abstain}} > U_0^{\text{spend}}$. Using Equation (3), this implies $u(\alpha s) < \delta \Delta V_1$. The $t = 1$ "doer" self prefers to spend if $U_1^{\text{spend}} > U_1^{\text{abstain}}$. Using Equation (4), this implies $u(\alpha s) > \beta\delta\Delta V_1$. Thus, a self-control problem exists if both conditions are met, such that the utility of gratification $u(\alpha s)$ falls within the region:

$$\beta\delta\Delta V_1 < u(\alpha s) < \delta\Delta V_1.$$

This region is non-empty for any $\beta < 1$.

**Details of Example in Section 3.2.** Assume that $r > \frac{1}{\delta} - 1$. In other words, the interest rate is sufficiently high with respect to the discount factor. This assumption ensures that repayment is sufficiently costly such that the borrower would not always choose to consume.

We search for the region of time-inconsistent preferences.

Case 1: $c < (1 + r)s$. The default cost is so low that the borrower will always default in period 2, so $V_1^{\text{spend}} = V_1^{\text{abstain}} = -c$. Therefore, $U_1^{\text{spend}} > U_1^{\text{abstain}}$ and $U_0^{\text{spend}} > U_0^{\text{abstain}}$. Spending is preferable from the perspectives of both periods 0 and 1.

Case 2: $c > (1 + \alpha)(1 + r)s$. The default cost is so high that the borrower will always repay in period 2, so $V_1^{\text{spend}} = -(1 + \alpha)(1 + r)s$ and $V_1^{\text{abstain}} = -(1 + r)s$. Under the assumption $r > \frac{1}{\delta} - 1$, $U_0^{\text{spend}} < U_0^{\text{abstain}}$, and the borrower always prefers to abstain from the perspective of period 0. From the perspective of period 1, however, when $\beta < \frac{1}{\delta(1+r)}$, i.e., the borrower is more present-biased, $U_1^{\text{spend}} > U_1^{\text{abstain}}$. So, the borrower prefers to spend from the perspective of period 1. In other words, these borrowers have their spending preferences reversed.

Case 3: $(1 + r)s < c < 2(1 + r)s$. First, observe that spending implies default, and abstinence implies no default. $V_1^{\text{spend}} = -c$ and $V_1^{\text{abstain}} = -(1 + r)s$. From the perspective of period 0, when $c/s < 1 + r + \frac{\alpha}{\delta}$, $U_0^{\text{spend}} > U_0^{\text{abstain}}$. From the perspective of period 1, when $\beta < \frac{\alpha}{\delta(c/s-1-r)}$, $U_1^{\text{spend}} > U_1^{\text{abstain}}$.

**Proof of Proposition 2.** The single-crossing assumption implies an increasing-difference relationship in future value derived from the two options. Let $\Delta V_1(c) = V_1(s, r_d, c) -$

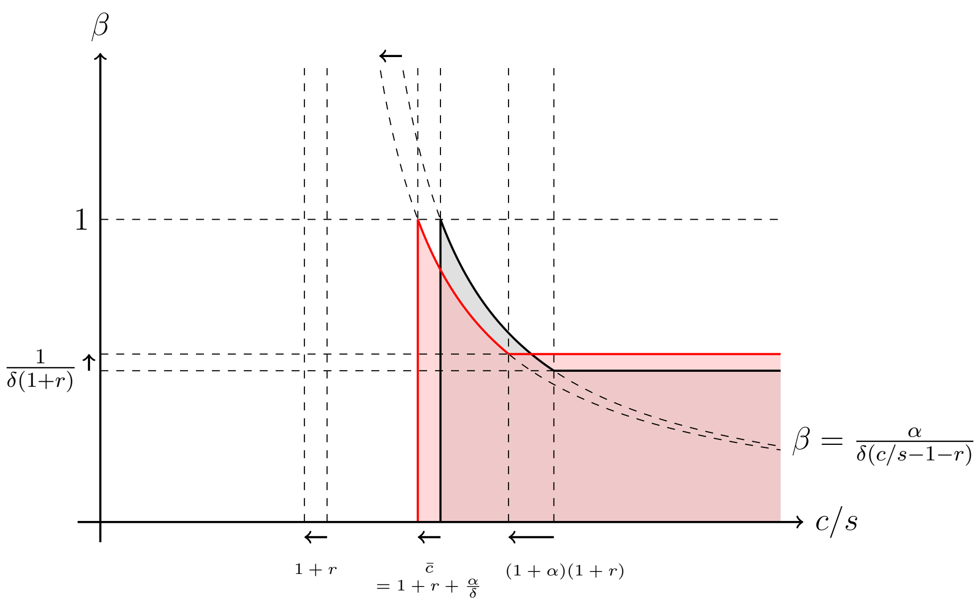
$V_1((1+\alpha)s, r_c, c)$ be the net gain in continuation value from abstaining. The single-crossing assumption means this net future gain is greater for the high-type:

$$\Delta V_1(c_H) > \Delta V_1(c_L) \tag{A.1}$$

The separating equilibrium is achieved by satisfying two incentive-compatibility (IC) constraints based on the borrowers' ex-ante ($t = 0$) utilities from Equation (2). A borrower of type $c$ will choose direct-pay if $U_0^{\text{abstain}} > U_0^{\text{spend}}$. The condition to choose Direct-Pay (Abstain) is $\delta\Delta V_1(c) > u(\alpha s)$. If the immediate consumption utility $u(\alpha s)$ falls between these two values: $\delta\Delta V_1(c_L) < u(\alpha s) < \delta\Delta V_1(c_H)$, the high-type borrowers will choose direct-pay, and low-type borrowers will choose cash.

**Effect of lower interest rate.** We illustrate the effect of a lower interest rate on the separating equilibrium in Figure A3. The lower interest rate shifts the cutoff $\bar{c}$ downward, expanding the pool of borrowers who choose direct-pay.

Figure A3: Effect of lower interest rate




*Notes:* The figure illustrates the effect of a lower interest rate on the separating equilibrium. The x-axis is the default cost $c/s$, and the y-axis is the present-bias parameter $\beta$.

**Proof of Proposition 3.** The first order condition yields

$$\frac{\partial u(\alpha s)}{\partial \alpha} + \beta\delta \frac{\partial V_1^{\text{spend}}}{\partial \alpha} = 0, \tag{A.2}$$

which characterizes the optimal propensity to spend $\alpha^*$ as an implicit function of $\beta$. Differentiating the FOC with respect to $\beta$,

$$\delta \frac{\partial V_1^{\text{spend}}}{\partial \alpha} + \frac{\partial \alpha}{\partial \beta}\Big(\frac{\partial^2 u(\alpha s)}{\partial \alpha^2} + \beta\delta \frac{\partial^2 V_1^{\text{spend}}}{\partial \alpha^2}\Big) = 0 \tag{A.3}$$

Because $\frac{\partial V_1^{\text{spend}}}{\partial \alpha} < 0$ and the term in the parentheses is also negative, $\frac{\partial \alpha^*}{\partial \beta} < 0$.

**Submodularity of $V_1(\cdot)$ in Equation (13) in the structural model.** The value of the loan at the beginning of the repayment stage, $V_1(s,r,c)$, is submodular in both $(s,c)$ and $(r,c)$. That is,

$$\frac{\partial^2}{\partial s \partial c} V_1(s,r,c) < 0 \text{ and } \frac{\partial^2}{\partial r \partial c} V_1(s,r,c) < 0. \tag{A.4}$$

We provide an intuitive explanation of this result. First, note that the value of the loan decreases in $s$ and $r$, *i.e.*, $\frac{\partial}{\partial s} V_1(s,r,c) < 0$ and $\frac{\partial}{\partial r} V_1(s,r,c) < 0$. Additionally, good borrowers with a high default cost $c$ are more likely to choose to make repayments, so their loan value is more responsive to changes in the monthly installment $m$. Because the monthly installment $m$ increases monotonically with the loan size $s$ and the interest rate $r$, the partials $\frac{\partial}{\partial s} V_1(s,r,c)$ and $\frac{\partial}{\partial r} V_1(s,r,c)$ are decreasing in $c$, giving rise to submodularity.

## A.2 Borrower Characteristics Balance Test

Table A9: Borrower Characteristics: Eligible vs. Ineligible Loan Types

| Variable | Eligible | Ineligible | StdDev | Cohen's $d$ |
|---|---|---|---|---|
| Annual Income | 80.60 | 83.00 | 94.50 | -0.03 |
| Debt-to-Income Ratio | 18.60 | 16.60 | 8.74 | 0.23 |
| FICO Score | 700.00 | 703.00 | 29.00 | -0.12 |
| Homeowner | 0.12 | 0.14 | 0.33 | -0.05 |
| Credit History Length | 15.70 | 15.80 | 7.71 | -0.01 |
| Inquiries (6 months) | 0.47 | 0.54 | 0.75 | -0.09 |
| Open Accounts | 11.70 | 10.70 | 6.01 | 0.16 |
| Revolving Utilization | 48.80 | 41.30 | 24.20 | 0.31 |

*Notes:* This table compares borrower and loan characteristics between loans eligible for the direct-pay option (e.g., debt-refinancing or credit-card-repayment loans) and those ineligible (general-purpose or other consumer loans). Eligibility is determined by loan purpose categories defined prior to the policy introduction. Eligible and ineligible borrowers are broadly similar across most observable dimensions, including income, DTI, credit score, and credit history, although eligible borrowers tend to have slightly higher debt burdens. Overall, these comparisons support the validity of the difference-in-differences design by showing that the control group (ineligible loans) provides a reasonable counterfactual for the treated group (eligible loans).

Table A10: Borrower Characteristics Before and After the Policy Introduction

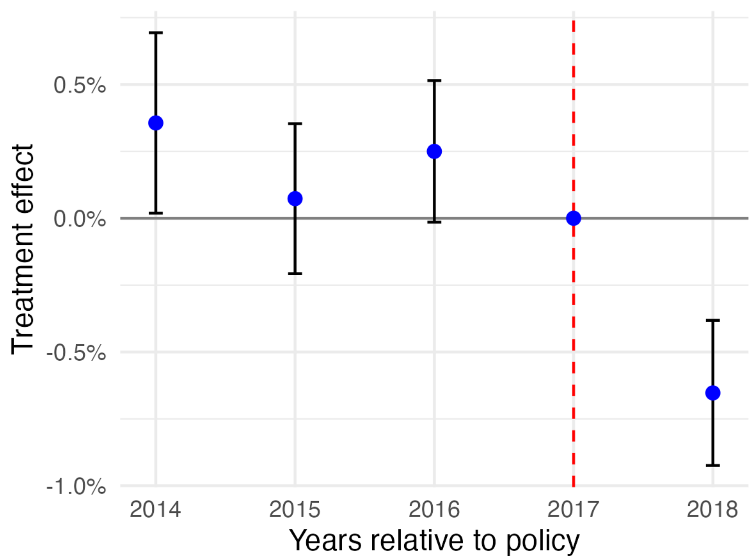
| Variable | Year 2017 | Year 2018 | StdDev | Cohen's $d$ |
|---|---|---|---|---|
| Annual Income | 79.63 | 81.05 | 177.69 | -0.01 |
| Debt-to-Income Ratio | 18.29 | 18.19 | 8.49 | 0.01 |
| FICO Score | 696.06 | 700.46 | 28.56 | -0.15 |
| Homeowner | 0.12 | 0.12 | 0.33 | -0.01 |
| Credit History Length | 16.23 | 15.72 | 7.70 | 0.07 |
| Inquiries (6 months) | 0.55 | 0.48 | 0.79 | 0.08 |
| Open Accounts | 11.53 | 11.52 | 5.90 | 0.00 |
| Revolving Utilization | 50.73 | 47.49 | 24.17 | 0.13 |

*Notes:* This table compares key borrower and loan characteristics for loans originated in 2017 (pre-policy) and 2018 (post-policy). Variables include loan amount, interest rate, annual income, debt-to-income (DTI) ratio, credit score (FICO), homeownership, credit-history length, recent credit inquiries, number of open credit accounts, and revolving credit utilization. Differences are generally small and statistically insignificant, indicating that the composition of borrowers did not change materially around the introduction of the direct-pay policy. These results suggest that the observed changes in default rates are unlikely to be driven by shifts in borrower quality or loan mix.

## A.3 Robustness and Parallel Trends in DiD Analysis

Table A11 reports robustness checks extending the pre-policy period to 2014–2017 and estimating both the baseline DiD and a time-varying treatment-effect specification. The estimated coefficients remain negative and statistically significant, confirming that the direct-pay policy continues to reduce default rates under alternative sample definitions. Figure A4 plots the dynamic treatment effects and shows no differential pre-trend before 2018 and a decline in defaults thereafter, supporting the validity of the parallel-trends assumption.

Figure A4: Time-Varying Treatment Effects and Parallel Trends




*Notes:* This figure plots the estimated coefficients and 95% confidence intervals from an event-study version of the difference-in-differences model, where each coefficient represents the relative change in one-year default rates for treated (eligible) loans compared with untreated loans in year t, using 2017 as the omitted baseline.

Table A11: Robustness of the Direct-Pay Policy Effect: Extended Pre-Period and Dynamic Treatment Estimates

| | One-year default | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treated | −0.008*** (0.001) | −0.014*** (0.001) | −0.014*** (0.001) | −0.147*** (0.010) | −0.263*** (0.010) | −0.261*** (0.015) | −0.014*** (0.001) | −0.273*** (0.018) |
| 2014 | | | | | | | −0.019*** (0.002) | −0.381*** (0.041) |
| 2015 | | | | | | | −0.007*** (0.001) | −0.138*** (0.024) |
| 2016 | | | | | | | −0.000 (0.001) | −0.009 (0.022) |
| 2018 | | | | | | | 0.008*** (0.002) | 0.125*** (0.036) |
| 2014 × Treated | | | | | | | 0.004* (0.002) | 0.045 (0.035) |
| 2015 × Treated | | | | | | | 0.001 (0.001) | 0.007 (0.021) |
| 2016 × Treated | | | | | | | 0.002 (0.002) | 0.050 (0.026) |
| 2018 × Treated | | | | | | | −0.007** (0.002) | −0.099** (0.031) |
| Loan amount | | 0.001*** (0.000) | 0.001*** (0.000) | | 0.025*** (0.001) | 0.025*** (0.001) | 0.001*** (0.000) | 0.025*** (0.001) |
| Term 3-year | | −0.003*** (0.000) | −0.003*** (0.001) | | −0.066*** (0.008) | −0.066*** (0.014) | −0.004*** (0.001) | −0.082*** (0.013) |
| log(Annual income) | | −0.013*** (0.000) | −0.013*** (0.001) | | −0.277*** (0.009) | −0.279*** (0.012) | −0.014*** (0.001) | −0.297*** (0.012) |
| Debt-to-income | | 0.001*** (0.000) | 0.001*** (0.000) | | 0.019*** (0.000) | 0.019*** (0.001) | 0.001*** (0.000) | 0.019*** (0.001) |
| Credit score (FICO) | | −0.000*** (0.000) | −0.000*** (0.000) | | −0.007*** (0.000) | −0.007*** (0.000) | −0.000*** (0.000) | −0.007*** (0.000) |
| Home ownership | | 0.002*** (0.001) | 0.002*** (0.001) | | 0.040*** (0.011) | 0.039*** (0.011) | 0.002** (0.001) | 0.033** (0.012) |
| Credit history length (years) | | −0.001*** (0.000) | −0.001*** (0.000) | | −0.014*** (0.001) | −0.014*** (0.001) | −0.001*** (0.000) | −0.014*** (0.001) |
| Credit inquiries (past 6 months) | | 0.013*** (0.000) | 0.013*** (0.000) | | 0.220*** (0.004) | 0.221*** (0.007) | 0.013*** (0.000) | 0.233*** (0.005) |
| Open credit accounts | | −0.001*** (0.000) | −0.001*** (0.000) | | −0.012*** (0.001) | −0.012*** (0.001) | −0.001*** (0.000) | −0.011*** (0.001) |
| Revolving credit utilization | | −0.000*** (0.000) | −0.000*** (0.000) | | −0.004*** (0.000) | −0.004*** (0.000) | −0.000*** (0.000) | −0.003*** (0.000) |
| Constant | 0.059*** (0.000) | 0.340*** (0.006) | 0.338*** (0.005) | −2.771*** (0.009) | 3.066*** (0.117) | 3.022*** (0.129) | 0.347*** (0.005) | 3.209*** (0.133) |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| R2 | 0.000 | 0.007 | 0.007 | | | | 0.008 | |
| Observations | 1530704 | 1530703 | 1530703 | 1530704 | 1530703 | 1530703 | 1530703 | 1530703 |
| Log Likelihood | | | | −319391.485 | −314231.172 | −314169.218 | | −313761.994 |

*Notes:* This table reports robustness checks using an extended pre-policy sample (2014–2017) and an event-study specification that allows time-varying treatment effects around the 2018 policy introduction. The dependent variable equals one if the loan defaults within one year of origination. All regressions include borrower- and loan-level controls (loan amount, term, log income, debt-to-income ratio, FICO, homeownership, credit history length, inquiries, open accounts, revolving utilization) and month fixed effects. Robust standard errors are clustered by origination month. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

## A.4 Survival Analysis of Loan Default

Table A12: Survival Analysis of Loan Default

| | Hazard ratio | | | | | |
|---|---|---|---|---|---|---|
| | 2018 | | | 2017 and 2018 | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Direct-pay | $-0.848^{***}$ | $-0.759^{***}$ | $-0.779^{***}$ | | | |
| | (0.024) | (0.024) | (0.024) | | | |
| Post cash | | | | $0.150^{***}$ | $0.139^{***}$ | $0.138^{***}$ |
| | | | | (0.012) | (0.012) | (0.012) |
| Post direct-pay | | | | $-0.699^{***}$ | $-0.625^{***}$ | $-0.637^{***}$ |
| | | | | (0.024) | (0.024) | (0.024) |
| Loan amount | | $0.023^{***}$ | $0.024^{***}$ | | $0.024^{***}$ | $0.024^{***}$ |
| | | (0.001) | (0.001) | | (0.001) | (0.001) |
| Term 3-year | | $-0.109^{***}$ | $-0.105^{***}$ | | $-0.095^{***}$ | $-0.091^{***}$ |
| | | (0.017) | (0.018) | | (0.013) | (0.013) |
| log(Annual income) | | $-0.266^{***}$ | $-0.270^{***}$ | | $-0.279^{***}$ | $-0.280^{***}$ |
| | | (0.019) | (0.019) | | (0.014) | (0.014) |
| Debt-to-income | | $0.010^{***}$ | $0.009^{***}$ | | $0.014^{***}$ | $0.014^{***}$ |
| | | (0.001) | (0.001) | | (0.001) | (0.001) |
| Credit score (FICO) | | $-0.008^{***}$ | $-0.008^{***}$ | | $-0.008^{***}$ | $-0.008^{***}$ |
| | | (0.000) | (0.000) | | (0.000) | (0.000) |
| Home ownership | | 0.007 | 0.008 | | 0.024 | 0.024 |
| | | (0.024) | (0.024) | | (0.017) | (0.017) |
| Credit history length (years) | | $-0.011^{***}$ | $-0.011^{***}$ | | $-0.010^{***}$ | $-0.010^{***}$ |
| | | (0.001) | (0.001) | | (0.001) | (0.001) |
| Credit inquiries (past 6 months) | | $0.272^{***}$ | $0.273^{***}$ | | $0.277^{***}$ | $0.276^{***}$ |
| | | (0.009) | (0.009) | | (0.006) | (0.006) |
| Open credit accounts | | $-0.015^{***}$ | $-0.015^{***}$ | | $-0.015^{***}$ | $-0.015^{***}$ |
| | | (0.002) | (0.002) | | (0.001) | (0.001) |
| Revolving credit utilization | | $-0.006^{***}$ | $-0.006^{***}$ | | $-0.005^{***}$ | $-0.005^{***}$ |
| | | (0.000) | (0.000) | | (0.000) | (0.000) |
| Month fixed effects | No | No | Yes | No | No | Yes |
| Pseudo-$R^2$ | 0.006 | 0.014 | 0.014 | 0.003 | 0.011 | 0.011 |
| Observations | 278046 | 278046 | 278046 | 528819 | 528819 | 528819 |

*Notes:* This table reports Cox proportional-hazard estimates of the effect of the direct-pay policy on the timing of loan default. The dependent variable is the time (in months) from origination to default or censoring at loan maturity. The hazard ratio below one indicates a lower risk of default. Columns (1)–(3) use the 2018 cohort and compare cash and direct-pay borrowers' default hazards through 2019, controlling for borrower and loan characteristics. Columns (4)–(6) pool the 2017 and 2018 cohorts to compare 2018 cash and direct-pay borrowers against the 2017 baseline. The key variable Direct-Pay equals one for loans disbursed directly to creditors; in the pooled regressions, Post Cash and Post Direct indicate 2018 cash and 2018 direct-pay loans, respectively, with 2017 cash loans as the omitted group. All specifications include controls for loan amount, term (3-year indicator), log annual income, debt-to-income ratio, FICO score, homeownership, credit-history length, credit inquiries in the past six months, number of open credit accounts, and revolving-credit utilization, as well as month-of-origination fixed effects. Standard errors are clustered by origination month. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

## A.5 Model Fit of Structural Estimation

Table A13: Model Fit of Targeted Moments in Structural Estimation

| Moment | Empirical | Fitted |
|---|---|---|
| Default in 2017 | 5.1% | 5.2% |
| Direct-Pay Choice 2018 | 25.9% | 26.1% |
| Default (Cash) in 2018 | 5.8% | 5.8% |
| Default (Direct-Pay) in 2018 | 2.6% | 2.6% |
| Default (Overall) in 2018 | 5.0% | 5.0% |

*Notes:* This table compares the empirical moments from the data (column "Empirical") to the corresponding moments generated by the estimated structural model (column "Fitted") for loans with a term of 3 years. The structural parameters are estimated via the Generalized Method of Moments (GMM), which minimizes the distance between these two sets of moments. The four targeted moments are: (1) the 2017 pre-policy default rate, (2) the 2018 direct-pay adoption rate, (3) the 2018 default rate for cash borrowers, and (4) the 2018 default rate for direct-pay borrowers. The "Default in 2018" row reports the aggregate default rate, which is an outcome of the four targeted moments.